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Price Prediction Line, Investment Signals and Limit Conditions Applied for the German Financial Market

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***Abstract*—**In the first decades of the 21st century, in the electronic trading environment, algorithmic capital investments became the primary tool to make a profit by speculations in financial markets. A significant number of traders, private or institutional investors are participating in the capital markets every day using automated algorithms. The autonomous trading software is today a considerable part in the business intelligence system of any modern financial activity. The trading decisions and orders are made automatically by computers using different mathematical models. This paper will present one of these models called Price Prediction Line. A mathematical algorithm will be revealed to build a reliable trend line, which is the base for limit conditions and automated investment signals, the core for a computerized investment system. The paper will guide how to apply these tools to generate entry and exit investment signals, limit conditions to build a mathematical filter for the investment opportunities, and the methodology to integrate all of these in automated investment software. The paper will also present trading results obtained for the leading German financial market index with the presented methods to analyze and to compare different automated investment algorithms. It was found that a specific mathematical algorithm can be optimized and integrated into an automated trading system with good and sustained results for the leading German Market. Investment results will be compared in order to qualify the presented model. In conclusion, a 1:6.12 risk was obtained to reward ratio applying the trigonometric method to the DAX Deutscher Aktienindex on 24 months investment. These results are superior to those obtained with other similar models as this paper reveal. The general idea sustained by this paper is that the Price Prediction Line model presented is a reliable capital investment methodology that can be successfully applied to build an automated investment system with excellent results.

***Keywords*—**Algorithmic trading, automated investment system, DAX Deutscher Aktienindex.

I. Introduction

CAPITAL investment is a sustained activity today. An impressive number of market participants are buying and selling every day on thousands of free markets. Traders, investors, different types of companies, private and public funds are participating in financial markets in order to make a profit from the difference between the buy and the selling price. Once electronic trading was widespread released, especially after 2011 when "investment firms on both the buy-side and sell-side were increasing their spending on technology for electronic trading" [1], a significant part of the capital investments is made completely automatically. The trading orders are built and sent almost instantly by servers running automated trading systems.

Algorithmic trading is the key in financial trading nowadays, as long as "large general financial volatility may increase uncertainty about the economic environment, with long-lasting effects as investors demand a higher risk" [2]. With increased price volatility on markets where "there is an exponential over-reaction to an action" [3], the trading decisions must be fast indeed. Special algorithms and methodologies are used in order to send the trading orders before a significant change in the price level. This paper will present one of these mathematical models specially designed for algorithmic trading.

Thousands of trading strategies compete to find the best way to buy and sell in order to make a profit. Related with the capital investment strategies for the stock markets, advanced studies and working models that can be used in algorithmic trading can be found in [4]-[7]. For the currency and commodities markets, reliable models and trading strategies can be found in [8]-[10]. Original investment strategies optimized for automated capital investment software can be found in [11]-[15].

The theory is simple: buy cheap and sell more expensive. To put it in practice is not easy nowadays, because of the price volatility, unexpected news released, and unexpected behavior of the significant market participants.

Dictionaries of trading rules and psychological practice to enhance the capital investment performance are since a long time on libraries. One of the essential books is [16], including several practical strategies that can be included in algorithmic trading in order to improve the mathematical models. Recommendation lines from notable authors can be found as: "buy the market after it's dropped; not after it's risen." [4] But when the market it's dropped enough? Also, when is the price too much higher, and it is preparing to change its direction? How to determine all of these in order to have a supportable risk? Moreover, how to automate the trading decisions, including all of these considerations? The method presented in this paper will offer answers to all these questions.

The algorithm presented in this paper is exclusively a mathematical model based on the price time series. It can be easily implemented in any automated trading system in order to automate the capital investment process. The model uses the cyclicality behavior of the time price variations to build a price prediction trend line called "Price Prediction Line." Trading signals will be built using the particularities of this function, in order to buy or to sell on the capital market depending on the predicted price tendency. Realistic price

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level predictions can also be made together with limit conditions in order to exit the investment positions before the trend changes its direction. The presented method will be compared with other models using trading results presented in the last part of the paper.

II. Price Cyclicality

The model presented in this paper will use the "Price Cyclicality function" noted as PCY [17]. Starting with the assumption that the price has a wave behavior with variable wavelengths, the model can be successfully applied for any volatile market. This hypothesis is in line with the real behavior of the investors in financial markets. After the price starts to increase, more market participants will open more buy positions that will grow the price continuously by increasing demand. After a while, some of them will start to close those trades in order to mark the profit. In that time interval, the price evolution slows down. At a certain time moment, more traders and investors will close their long positions detecting the slowdown in the price evolution. More sell orders than the buy orders will arrive on the market. A reversed tendency will be present sooner or later in the price behavior. It is a cyclical phenomenon which will be seen in the price evolution. Increasing and decreasing demand intervals are present in each market, similar to wave propagation in time. Because the decisions do not have constant repeatability, the price wave will have a variable wavelength. The model presented in this paper can be adapted automatically to this cyclical behavior. It will use the price time series evolution and different functional parameters which are optimized for each capital market.

The Price Cyclicality Function (PCY_i) is mathematically defined for each time price series interval (i) by the next recurrent formula, starting from [17]:

$$PCY_i = \alpha\left(\Delta_i - PCY_{i-1}\right) + PCY_{i-1} \text{ where } PCY_0 = 0 \quad (1)$$

where

$$\Delta_i = \frac{max_i - \xi_i}{max_i - min_i} \text{ where } \xi_i = Ma_i - ma_i \quad (2)$$

and

$$min_i = \min_{k=i}^{i-n}\left(Ma_k - ma_k\right) \quad (3)$$

$$max_i = \max_{k=i}^{i-n}\left(Ma_k - ma_k\right) \quad (4)$$

Ma_i and ma_i are two moving averages [18] with different periods (*Pma* and *Pma*, where *PMa* < *Pma*), and (n) is the number of the time intervals considered in the time price series, associated with the period of the presented model. These three parameters (PMa, Pma, and n) are functional parameters that will be optimized for each capital market and for each timeframe used in order to obtain the maximal capital efficiency for a minimal capital exposure, as we will see in a further chapter. The PCY is represented in Fig. 1 for a daily evolution of the Deutscher Aktienindex DAX30, the main index of the Frankfurt Stock Exchange [19].

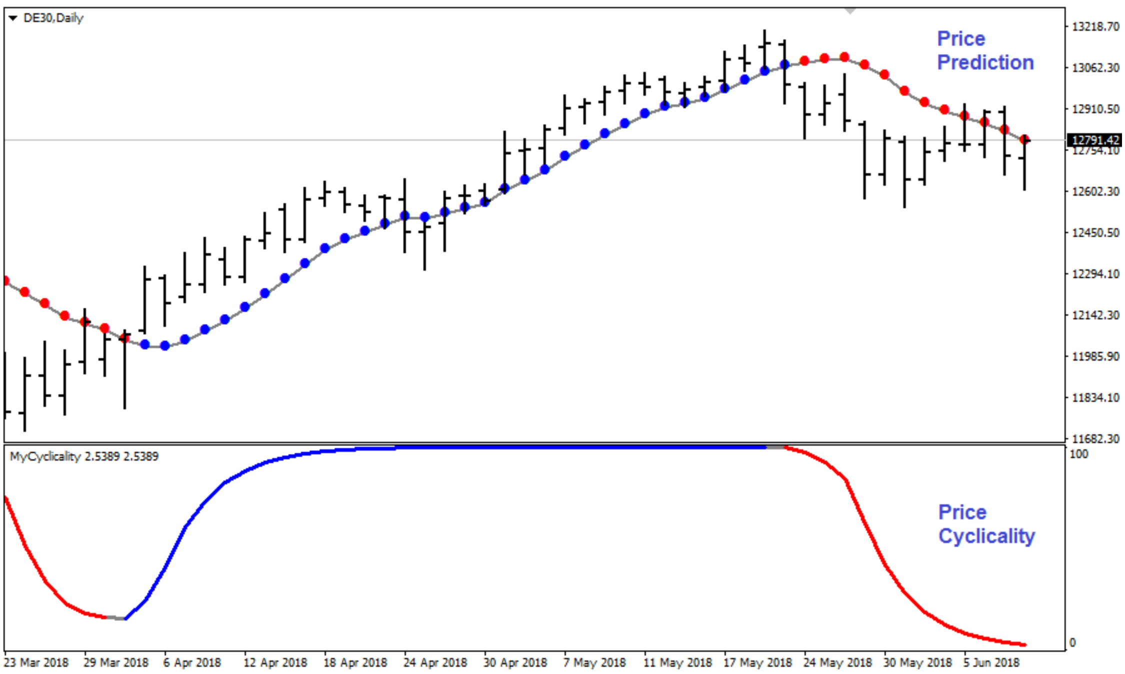

Fig. 1 PCY and Price Prediction Line

The PCY has some important properties. The (PCY_i) values are limited into the interval [0;100]. The function presents well defined ascending and descending intervals depending on the price tendency and most important, the function has asymptotic behavior on the overbought and oversold price intervals. What is missing from the PCY model is a way to predict the price level. The PCY function predicts with enough accuracy, only the change in the price. The model developed and presented in this paper proposes to predict the price behavior for the next time intervals together with a predicted price value level. To do this we will transform the PCY back into the price space using the next transformation function:

$$PPL_i = PCY_i \cdot \left(Pmax_i - Pmin_i\right)/100 + Pmin_i \qquad (5)$$

The new function obtained (PPL_i) is the Price Prediction Line, a very useful function which will be used to obtain a price prediction level, as we will see in this paper. Once the terms ($Pmin_i$) and ($Pmax_i$) represent the maximum and minimum price values on the current monotony interval of the Price Cyclicality Function (PCY) is given by (1), after simple mathematical considerations we can see that the PPL_i values are defined in the price space.

In very volatile price movements, the Price Prediction Line given by (5) needs an attenuation process in order to have a smoothed evolution. For this step we can apply mathematical attenuation methods as the smoothing with Spline line interpolations [20], polynomial or trigonometric interpolations [21] or simple, exponential or weighted moving averages [18] with a small period. The result using trigonometric interpolation to attenuate the PPL_i values for DAX30 index are presented n Fig. 1.

III. Price Prediction Line

The Price Prediction Line obtained after smoothing the transformation function (5) has ascending and descending intervals depending on the price behavior. The monotony intervals are determined by an increased values of $Pmax_i$ and $Pmin_i$ on an increasing interval of the PCY_i.

Due to the way the Price Prediction Line (PPL) function is built, (5), usually the minimum values of the price are attached to the PPL levels on the ascending intervals, and the maximum values of the price are usually attached with the PPL levels on the descending intervals.

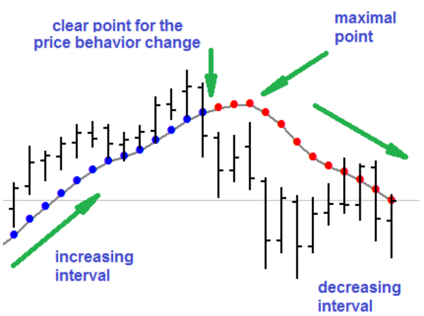

Fig. 2 Clear point for the price behavior change

Intentionally the PPL is plotted in two colors depending on the price cyclicality ascending or descending intervals. As we can see, the monotony intervals of the prediction line are not the same as the monotony intervals of the cyclicality function. The maximum and minimum points of the prediction line are delayed. The PPL is plotted in blue for the ascending periods of the PCY function, in order to keep the advantage of the monotony of the cyclicality function. Similarly, the PPL is plotted in red for the descending intervals of the PCY function. With all of these, we will have a clear point for the price behavior change, highlighted by the changing in color or the prediction line.

As we can see in Fig. 2, the price change behavior point is revealed before the maximum point of the PPL. In the moment when the PPL line changes its color, meaning the PCY function changed its monotony, the exit decisions from the buy positions can be met since a price descending interval is about to arrive. The color of the PPL is associated with the trend behavior property. In the same way, in Fig. 3, we can see that the ascending interval is announced by the prediction line before its minimum point. In addition, once the color of the line is changed, the prediction line values will be under the price level, as a minimum value for the buy price level where the trend behavior can be changed again.

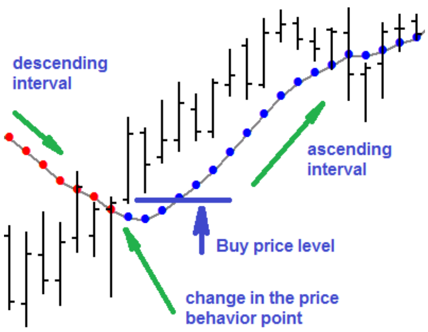

Fig. 3 Buy price level decided by the PPL

Considering the above, one can think that the PPL is only a colored line function depending on the PCY. After detailed studies, it was found that the PPL makes a better prediction in comparison with other models as moving averages. In Fig. 4, it is presented a comparison between the PPL and usually used moving averages. In Fig. 4 are drawn together the PPL line with a period of 20-time intervals and the simple and exponential price moving averages for the same period, on a time price series expressed on a daily-bases interval for a 52 days evolution of the Frankfurt Stock Exchange Deutscher Aktienindex DAX30.

As we can see, the PPL is a better approach to real-time price series values. Sometimes the simple or exponential moving averages monotony can predict the price behavior. However, a comparison of the current price level with the values of these moving averages in order to make a trade decision can involve a considerable delay. The PPL values are more close to the real price values, especially in the longer trend intervals. Besides, the specificity of the PPL can give us more accurate information about the price change behavior before the moving averages to start to change their monotony.

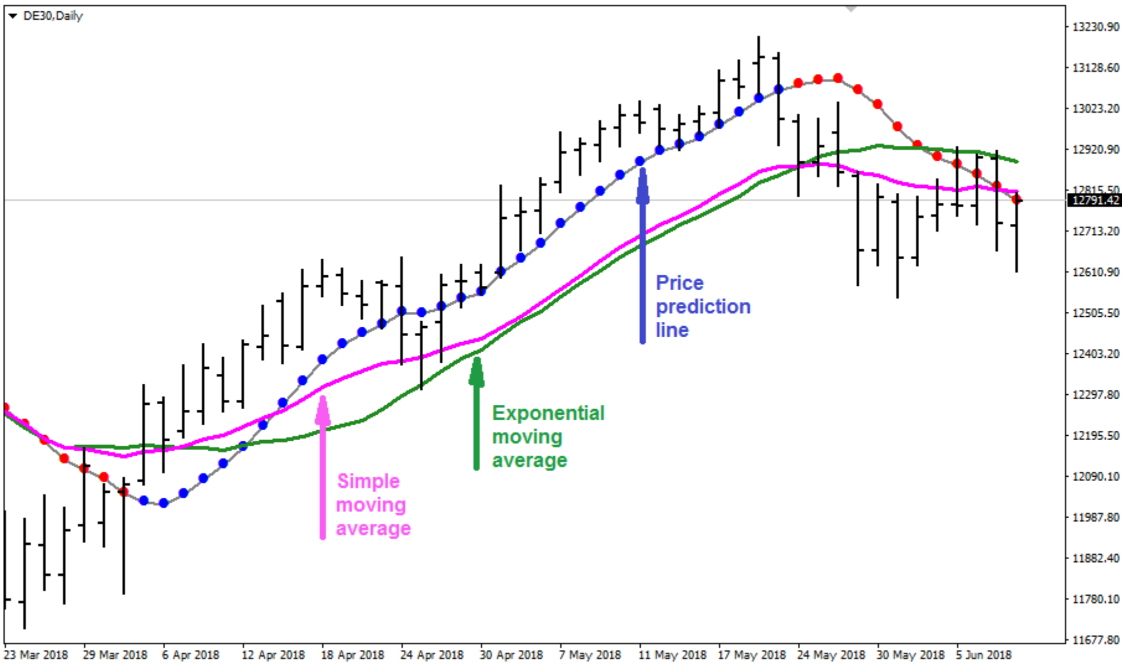

Fig. 4 Comparison between the PPL and moving averages

To trust the PPL, we also need a mathematical validation. This confirmation is given by Pearson's correlation coefficient [22] between two statistical series. Once our model tries to predict the minimal value of the price for the ascending intervals and the maximum values of the price for the descending intervals, the correlation coefficient can be adapted to this logic for our case with:

$$r = \frac{\sum_{i=1}^{N}(q_i - \overline{q})(PPL_i - \overline{PPL})}{\sqrt{\sum_{i=1}^{N}(q_i - \overline{q})^2}\sqrt{\sum_{i=1}^{N}(PPL_i - \overline{PPL})^2}} \tag{6}$$

where

$$q_i = low_i \text{ if } PCY_i > PCY_{i-1} \tag{7}$$

and

$$q_i = high_i \text{ if } PCY_i < PCY_{i-1} \tag{8}$$

in which the values (low_i) are the minimum price level and ($high_i$) represent the maximum price level for each (i) time interval included in the time price series. Comparing if the next price values are higher than the previous minimum price interval for an ascending period of the PPL, and evaluating if the next price values are lower than the previous high price value for a descending period of the PPL, the correlation coefficient has values between 0,583 and 0,999 for the DAX30 market depending on the time frame used and the period used to build the model. The values mentioned were obtained for periods (N) between 10 and 50-time intervals. The time frames used were 5 minutes (5M), 15 minutes (15M), 30 minutes (30M), one hour (1H), 4 hours (4H) and one day (1D). The historical time series computed were between 01.01.2010 and 31.06.2019. Higher values for the correlation coefficient were obtained for longer time frames. With these values for the correlation coefficient, it can be said that a direct and strong correlation between the price evolution and the PPL exists. The PPL values will predict the minimal local price values for the ascending intervals. Somewhere on these values, the price will change the behavior to a descending interval. Similarly, on descending price movements, the PPL will predict the local maximal price values.

In Fig. 5 is presented a code sample of the MetaQuotes Language [23] for the PPL. For simplicity, the code includes an attenuation process of the PPL values using an exponential moving average. Also, for simplicity, the *Signal* vector takes 0 and 1 values depending on if the price behavior is up or down. Sample code for the PCY can be found in [17].

IV. Price Prediction

The majority of the prediction models for algorithmic trading are indicating a price level for the next time intervals. After a buy trade was opened, the traders or the automated trading software procedures are waiting the price to rich that level in order to close the trade. Sometimes the predicted price level is never reached and the trade is turning into a loss trade. The model presented in this paper will work differently in order to assure the profit expectancy.

```
int start()
   {for(int i=Bars-MyPeriod;i>=0;i--)
       {Cycle[i]=iCustom(NULL,0,"MyCyclicality",MyPeriod,0,i);
        if(Cycle[i]>=Cycle[i+1]){Pmax=iHigh(NULL,0,i);}
        if(Cycle[i]< Cycle[i+1]){Pmin=iLow(NULL,0,i);}
        Buffer[i]=Cycle[i]*(Pmax-Pmin)/100+Pmin;
        Prediction[i]=iMAOnArray(Buffer,0,MyPeriod/2,0,MODE_EMA,i);
        if(Cycle[i]>=Cycle[i+1]){UpBuffer[i]=Prediction[i]; DnBuffer[i]=0; Signal[i]=1;}
                            else{DnBuffer[i]=Prediction[i]; UpBuffer[i]=0; Signal[i]=0;}}
    return(0);}
```

Fig. 5 MetaQuotes Language code for PPL

First of all, this prediction model will predict the next price behavior and the moment when the price changes its tendency. When the PPL turns from the red to the blue zone, an ascending interval for the price is arrived. The minimal price level where the price can change again its behavior is defined by future values of the PPL. When the PPL turns from the blue interval into the red values, a decreasing price interval will be on the next scenario. The price will descend under the PPL values, and that is the last good moment to close the long trades. In this way, an automated trading procedure can be organized in order to automate the capital investment process. Similarly, for the markets where short trades can be considered, in the presence of a significant descending trend, sell signals can be built when the PPL turns from the blue zone to the red one. The maximal entry price level will be defined by the values of the PPL. The exit points will be met when the PPL turns again from the red interval into the blue one. Of course, the red and blue color properties were used here for the visual presentation. In algorithmic trading, these are properties defined as buy and sell internal properties of the PPL class.

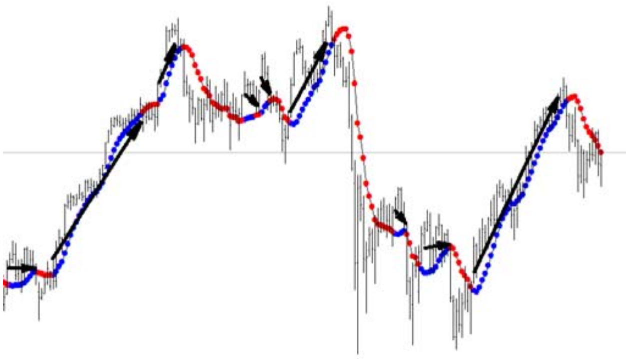

Fig. 6 Buy positions managed by the PPL

In Fig. 6 are displayed more consecutive buy trades managed by the PPL. As we can see, using the exit conditions provided only by the PPL intervals, not all trades are profitable. Additional conditions must be met for this target, as we will see in the next chapters. However, on a well-capitalized market, the PPL catches early the most important trades. The exit decisions are a separate subject later in this paper.

V. Investment Signals

By trading or investment signal, we understand a Boolean variable with *true* value if a trade can be opened. Depending on different conditions imposed with the *PPL* and *PCY* functions, in direct correlation with the price evolution and market behavior, these variables will permit to automate the trading process. A buy signal is a signal that will decide if a buy trade can be opened. A sell signal will be the signal for a short trade. According with the PPL significance, the buy signals can be defined as:

$$BuySignal_i = (p_i > PPL_i) \wedge (\overline{PPL_i} = 1) \wedge (\overline{PPL_{i-1}} = 0) \quad (9)$$

where (p_i) are the price values and PPL_i are the PPL values for each (i) time interval. In (9) $\overline{PPL_i}$ are the values for the property associated with the color of the PPL providing the information about the PCY function monotony. These last values can be set in many ways. Boolean variables are the easiest way. We consider here 1 values for the ascending periods of the PCY function and 0 values for descending intervals of the PCY.

The trading signals made by (9) open trades when the local price trend is changed from a descending interval to a new increasing-price interval, in order to buy the equity near a local minimum point and to wait for the price growth. This scenario is for those algorithmic trading procedures that ask a relatively small number of trades and try to keep the opened positions as long as possible to catch the big movements of the market. For high-frequency trading procedures, the signal made by (9) makes a reduced number of trades, and because in these cases the profit target is a small one. For high-frequency trading procedures, an additional signal type is needed as long an uptrend is present:

$$BuySignal_i = (p_i > PPL_i) \wedge (\overline{PPL_i} = 1) \wedge (\overline{PPL_{i-1}} = 1) \quad (10)$$

Equation (10) makes new trades even on the last section of a trend which is not a good setup. Additional limit conditions must be imposed to avoid these cases, as we will see in the next chapter. In this section we have presented buy investment signals, the most used trading signals in the stock markets. For those markets where sell trades can be considered profitable, especially for contract for differences (CFD) investment procedures, the sell trading signals are built similarly with (9) and (10), considering the descending periods of the PPL.

VI. Limit Conditions

Automated trading systems involve different types of capital investment strategies and methodologies. One of the most used algorithmic trading procedures opens a trade and wait for the market as long as possible if the buy signal is present. For these, the PPL gives proper entry and exit signals. The entries will be made when the PPL turns in blue and will exit the trades when the PPL turns into the red zone. The price level for entry and exists are given by the PPL values. These trading signals are made by (9). Not all trades will be profitable as we will see in the last chapter, but the methodology tries to catch some big trades in order to cover all the small losses and to make a profit.

For high-frequency trading procedures, which make a significantly large number of tiny trades, the trading entries are made by the trading signals (10). Because these signals open trades even on the last part of the trend, when the price prepares to turn into the descending zone, additional limit conditions must be imposed in order to ensure that the entry point is good enough in order to make that small profit and to avoid essential losses.

A. Entry Limit Conditions

In practice there are cases when the high price volatility can produce exception cases. One of these cases is presented in Fig. 7. This is the case of the DAX30 Index market at 7 June 2016 when the price made a significant correction in the up direction in a very small time interval. The PPL turns form the red zone into the blue at very high values of the price. The trading signals made by (9) produced an entry point on the top level price figured in Fig. 7. After that, the market reversed strongly in down direction, fact signalized by the PPL which produced a small gradient evolution and turned into the red zone after a while, without the price to recover the losses on those days. The strange evolution is due significant volatility on the currency market following the Brexit news [24].

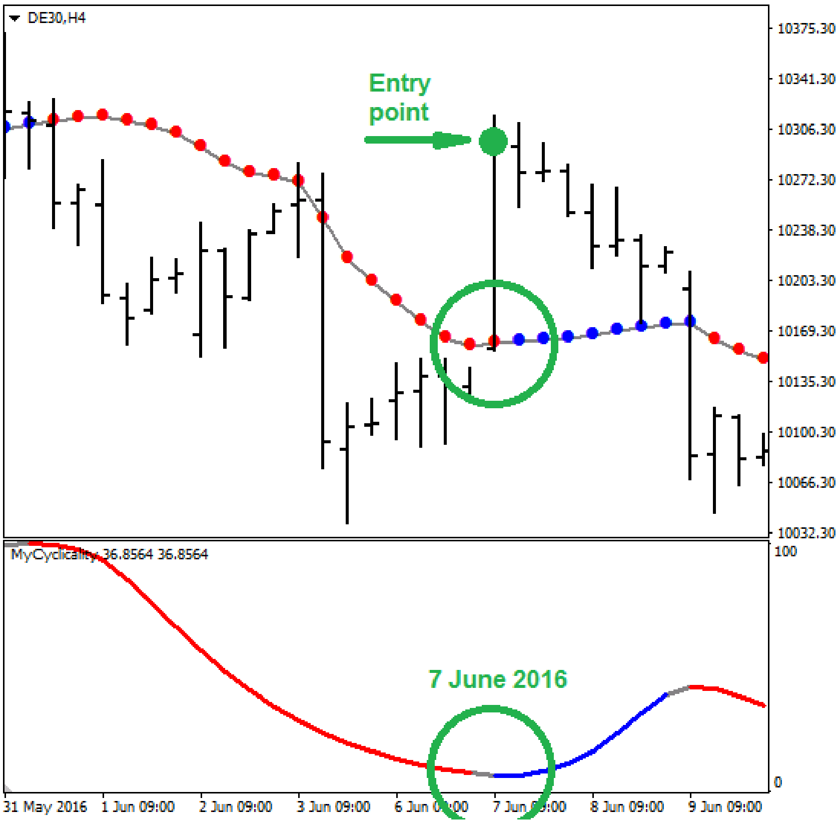

Fig. 7 Volatility exceptions with the PPL

To avoid cases like the one presented above, a limit condition imposed for the distance of the price from the PPL are used:

$$BuySignal_i = (p_i > PPL_i) \wedge (\overline{PPL_i} = 1) \wedge (\overline{PPL_{i-1}} = 0) \wedge (p_i < PPL_i + \delta) \tag{11}$$

and for high-frequency trading:

$$BuySignal_i = (p_i > PPL_i) \wedge (\overline{PPL_i} = 1) \wedge (\overline{PPL_{i-1}} = 1) \wedge (p_i < PPL_i + \delta) \tag{12}$$

where δ is the distance from the PPL_i accepted to be viable for opening a trade into the risk level accepted. The functional parameter δ can be optimized for each market, depending on the exposure capital level, using the historical time price series for a long interval of time. The limit conditions imposed by $(p_i < PPL_i + \delta)$ will filter the trading signals made by (9) and will allow only those trades with the price level under a limit. From this reason, we call these conditions as to be limit conditions. A more convenient graphic representation of these types of limit conditions is presented in Fig. 8.

Looking Fig. 8, we can see that, on a long trend, the price has the tendency to go up and to make new maximum points together with the PPL. Due to the construction of the PPL, the minimal values of the price will be in the zone of the PPL_i values, and the price tries to exceed these values and to make new local picks. On a normal trend zone, after a new minimum in the narrow of the PPL_i values, a new maximum will be made in one of the next time intervals if the price does not change its behavior. Using this idea the trading signals made by (12) work.

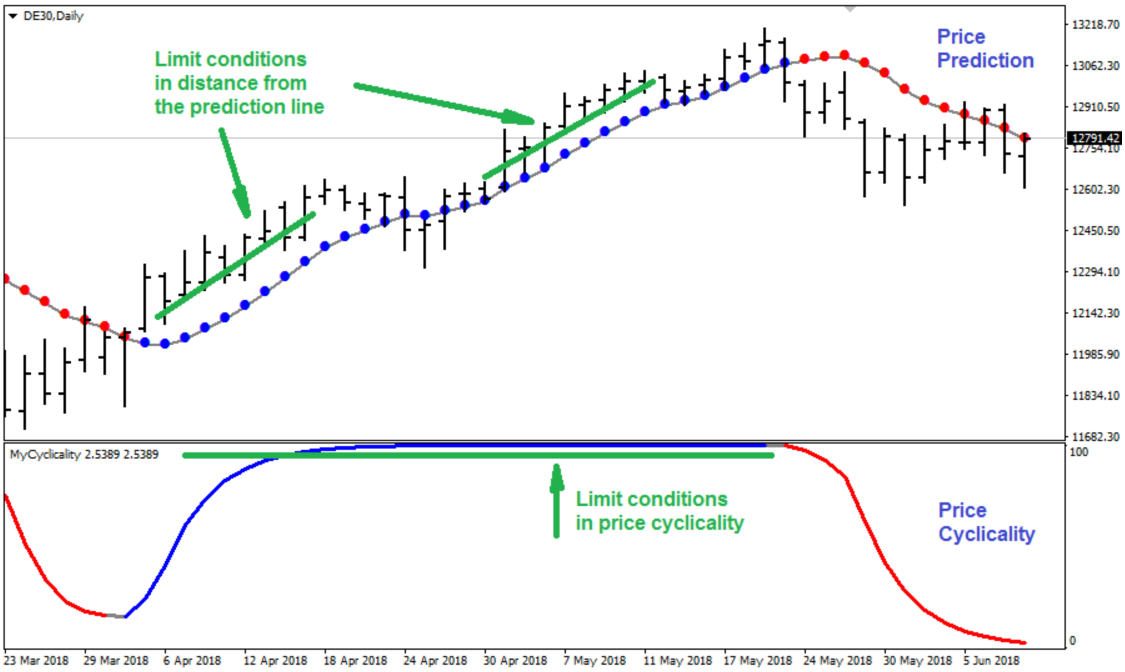

Fig. 8 Limit conditions depending on the PPL and PCY functions

When the price decreases under the δ distance from the PPL_i, the high-frequency trading procedure will open a new trade. This position will be closed on one of the next time intervals when the price makes a new local point, once the profit target is small. The high-frequency trading procedure will wait for the price to turn back into the δ distance from the PPL_i and will open a new trade, and so on, until the behavior of the price will be changed. With a good optimization for the δ, the strategy works for a large number of markets.

The second type of limit conditions imposed with the PP line is regarding the gradient of this function. As we have resented in Fig. 7, evolution with a small grading of the PPL indicates a weakness of the price trend. A limit condition in the gradient of the PPL function is imposed to avoid opening trades in cases like these:

$$\begin{aligned} BuySignal_i = (p_i > PPL_i) \wedge \left(\overline{PPL_i} = 1\right) \\ \wedge \left(\overline{PPL_{i-1}} = 1\right) \wedge \left(PPL_i - PPL_{i-1} > \xi\right) \end{aligned} \tag{13}$$

where ξ is the minimum gradient value for the PPL function to be considered strong enough in order to open a trade at a specified risk level. The ξ parameter can be considered in direct correlation with the power of the price trend. The filter in the power of the trend is imposed by the term $(PPL_i - PPL_{i-1} > \xi)$. This can be used with good results in order to filter any other trading signal. Trading results for high-frequency trading procedures made with these formulas will be presented in the last chapter.

For high-frequency trading procedures, limit conditions can be imposed using the PCY function as presented in [17]. To exit from the trades and to stop making new trades in high-frequency trading, the PCY function is limited in values as it is displayed in Fig. 8. However, these conditions cut a significant number of trades, especially for those cases when a long-time trend is present when the asymptotic section of the PCY function is long.

More limit conditions can be described with additional algorithms based on the direct of inverse Fished transform of the price, presented in [11] and [12]. In these cases also the limits are too restrictive for long trends because they are imposed only in the asymptotic stage of those indicators. The PPL function permits a new kind of limit conditions which can be combined with all the others mentioned.

B. Exit Limit Conditions

Based on this PPL behavior and the price movement near the prediction function levels, the exit conditions can be imposed as:

$$BuyExit_i = \left(\overline{PPL_i} = 1\right) \wedge \left(p_i > PPL_i + \varphi\right) \vee \left(\overline{PPL_{i-1}} = 0\right) \quad (14)$$

where φ is a functional parameter that can be optimized for each traded capital market using a repetitive procedures with a large historical time price series interval. The parameter φ is the maximal distance of the price from the PPL function where the price is considered high enough in order to wait the next local minimum point. The limit conditions (14) can be used with good results to automate the exit trading decisions for buy trades made with any other trading strategy both for algorithmic trading and high-frequency trading procedures. For those market cases in which sell trades can be considered, the limit conditions in order to exit the short trades can be expressed with:

$$SellExit_i = \left(\overline{PPL_i} = 0\right) \wedge \left(p_i < PPL_i - \varphi\right) \vee \left(\overline{PPL_{i-1}} = 1\right) \quad (15)$$

The limit conditions imposed by (14) and (15) on daily or four-hour time frames can also be combined with the limit conditions presented in [17], [11], and [12] imposed in a smaller time frame as one hour or even lower, in order to filter all overbought and oversold trades.

VII. Trading Results

In this section we will present some trading results obtained with the trading signals presented in above. The exit conditions presented in previous chapter were also included in the algorithmic trading procedures. The results were obtained using TheDaxTrader [25], an automated trading system that uses the PPL in order to generate buy trades for DAX30 index [19].

The results presented in Table I were obtained for the time period between 1 June 2015 and 31 May 2018. An additional condition was imposed for the entry trades regarding the hourly intervals between 8:00 and 16:00 coordinated universal time (UTC), Monday to Friday, in order to ensure the liquidity on the market. The DAX30 index was traded as a CFD with a spread of 1 point. For simplicity, the trades were made into an account with no leverage. The capital risk was managed using the "Global Slot Loss Method" [26]. The trading signals in Table I were assembled into four-hour time frame interval.

TABLE I
Trading Results for the PPL Methodology

Signal	Target	Positions	Profit	Drawdown	RRR
(9)	10 points	203	1,230	1,495	1:0.82
(11)+(14)	10 points	179	1,939	845	1:2.29
(11)+(14)	20 points	122	2,683	846	1:3.17
(11)+(14)	50 points	60	3,318	1,032	1:3.21
(13)+(14)	10 points	101	1,199	796	1:1.50
(13)+(14)	20 points	101	2,423	796	1:3.04

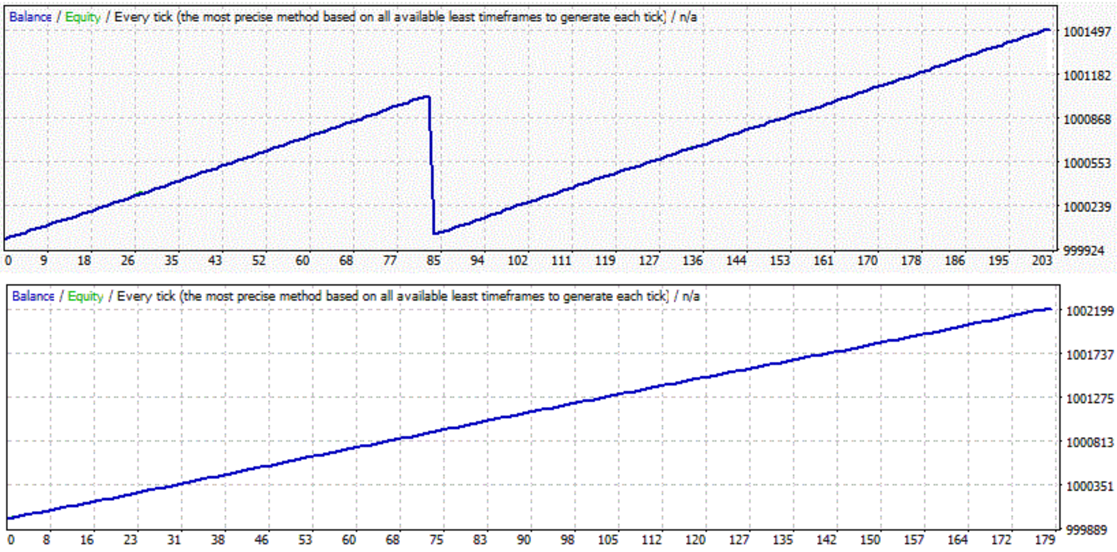

Fig. 9 Capital evolution with and without PPL limit conditions

The results presented in Table I are obtained using (11) for δ=10 and (14) for φ=100. In Fig. 9 is represented the capital variation for the trading case with (9) without the limit entry conditions and the same variation for the case for (11) using the limit conditions. As we can see, the limit conditions have successfully filtered the exception case presented in Fig. 7 which produced a heavy loss in the trading case with (9) without limit conditions. Even the number of trades is lower using the limit conditions, the profit is higher and the risk to reward ratio (RRR) is considerably improved for all cases using the limit conditions for the trading entries.

Trading with (11) and (14) for targets higher than 20 points we do not obtain a significant increase in RRR. In addition, using longer targets will produce longer trades. Values higher than 20 pips can be used for automated investment system instead high-frequency trading systems.

Working with signals made by (13) and (14) on volatile markets need sometimes additional conditions. In a volatile market, after a new trend was established and the PPL changes its color, entries can be made on points too far away the PPL or in the last part of the trend where the price is near the turning point. Additional limit conditions to entry and to exit the trades can be imposed. In this section are presented results obtained using the same PPL strategy applied in two time frames in the same time. The results in Table I were obtained applying (13) and (14) on one and four-hour time frames. When the buy trading signals were true for the both time frames, a new trade was opened with a ten points target.

VIII. Conclusions

The PPL can be built based on the local minimum and maximum points of the price time series using the PCY and a transformation function into the price space. The strong and direct correlation between the *PPL* function and the price movement indicates that the monotony of the *PPL* function can give us a strong indication about the price direction for the next intervals. Besides, the *PPL* has an additional property which is given by the monotony of the *PCY* function used to build the transformation. Reading the evolution of the *PPL* function together with the significance of the *PCY* function, trend decision can be made automatically by building logical trading signals.

The PPL function predicts the direction of the next price evolution and the moment when the trend will be changed. The values of the PPL function are more close to the price level than the moving averages and the PPL can be used to estimate the next possible price level where the new trend will start. The gradient of the PPL function is also a good indicator, being in strong relation with the power of the existing price trend and with the amplitude made by the price movements. High values for the gradient will indicate a strong price tendency. Low values of the gradient will indicate weak price movements. An exit signal can also be automated based on the PPL function gradient.

Limit conditions in order to filter the entry trades can be built using the PPL function, which can be used as price level reference. A higher value of the price, too far away the PPL levels can indicate a local maximum point and is a reasonable limit signal for exiting the trades. The limit conditions and the exit conditions based on the PPL function can be automated using functional parameters that are optimized for each traded market in order to reduce capital exposure and to maximize the profit. All PPL limit conditions can be used in order to filter any other type of trading signal. The model presented can be applied in any time frame for any financial market. The PPL can be easily automated in order to be included in any automated trading system, the model being exclusively a mathematical model based on the time price series.

References

[1] ISITC, International Securities Association for Institutional Trade Communication, 2011 Member Survey, March 12, 2012. Available on http://www.isitc.org
[2] Funke, N., Goldstein, A., Financial Market Volatility, Intereconomics Journal, volume 31, Issue 5, 1996, pp. 215-220. DOI: 10.1007/BF02927152
[3] Peters E., Chaos and Order in Capital Markets. A New View of Cycles, Prices and Market Volatility, 1996, John Wiley & Sons Inc., ISBN 0-471-13938-6
[4] Connors L., Alvarez C., Short term trading strategies that work. A Quantitative Guide to Stock Market Behavior, US: Trading Markets Publishing Group, 2009, ISBN 978-0-9819239-0-1
[5] Connors L., Sen C., How Markets Really Work – A Quantitative Guide to Stock Market Behavior, US: Connors Research Group, 2004, ISBN 978-0-9755513-1-8
[6] Connors L., Alvarez C., High Probability ETF Trading – 7 Professional Strategies to Improve Your ETF Trading, US: Connors Research, 2009, ISBN: 978-0-615-29741-5
[7] Connors L.A., Best Trading Patterns, The Best of the Professional Traders Journal, US: M. Gordon Publishing Group, 1999, ISBN: 0-9650461-0-2
[8] Lien K., Day Trading and Swing Trading the Currency Market. Technical and Fundamental Strategies to Profit the Market Moves. US: John Wiley & Sons, 2009, ISBN: 978-0-470-37736-0
[9] Lien K., The Little Book of Currency Trading. How to Make Big Profits in the World of Forex, US: John Wiley & Sons, 2011 ISBN: 978-0-470-77035-1
[10] Cheng G., 7 Winning Strategies for Trafing Forrex. Real and actionable techniques for profiting from the currency markets. GB: Hariman Trading, 2007 ISBN: 978-0-857190-90-1
[11] Păuna C., Reliable Signals Based on Fisher Transform for Algorithmic Trading. Romania: Timișoara Journal of Economics and Business. Volume 11, Issue 1/2018 ISSN: 2286-0991. West University of Timișoara. DOI: 10.2478/tjeb-2018-0006 Available at: https://tjeb.ro
[12] Păuna C., Reliable Signals and Limit Conditions for Automated Trading Systems. Romania: Review of economic and Business Studies. Volume XI, Issue 2/2018. ISSN: 1843-763X. Alexandru Ioan Cuza University Press. DOI: 10.1515/rebs-2018-0070 Available at: http://rebs.feaa.uaic.ro
[13] Păuna C., Smoothed Heikin-Ashi Algorithms Optimized for Automated Trading Systems, Austria: Proceeding of the 2nd International Scientific Conference on IT, Tourism, Economics, Management, and Agriculture. ITEMA 2018. Graz University of Technology. Available at: https://itema-conference.com
[14] Păuna C., Low risk trading algorithm based on the price cyclicality function for capital markets. Romania: 13th International Conference on Business ExcellenceAt: FABIZ, ASE, Bucharest DOI: 10.2478/mmcks-2019-0006
[15] Păuna C., Additional Limit Conditions for Breakout Trading Strategies. Romania: Informatica Economica Journal. Volume 23, Issue 2/2019. DOI: 10.12948/issn14531305/23.2.2019.03 Available at: http://revistaie.ase.ro
[16] Ward S., High Performance Trading. 35 Practicaal Strategies and Techniques to enhance Your Trading Psychology and Performance. GB: Hariman House 2010 ISBN: 978-1-905641-61-1
[17] Pauna C., Lungu, I., Price Cyclicality Model for Financial Markets. Reliable Limit Conditions for Algorithmic Trading, Romania: Economic computation and economic cybernetics studies and research, Volume 52, Issue 4/2018. DOI: 10.24818/18423264/52.4.18.10 Available at: http://ecocyb.ase.ro
[18] Cox, D.R. Sir, Prediction by Exponentially Weighted moving Averages and Related Methods, 1961, Journal of the royal Statistical Society, Series B, Vol. 23, No. 2, pp. 414-422
[19] Börse, Frankfurt, Frankfurt Stock Exchange Deutscher Aktienindex DAX30 Components, 2019. Available on: http://www.boerse-frankfurt.de/index/dax
[20] Reinsch, C., Smoothing by Spline functions, Numerische Mathematik, Volume 10, Issue 3, pp 177–183, ISSN 0945-3245, 1967, DOI https://doi.org/ 10.1007/BF02162161
[21] Berbente, C., Mitran, S., Zancu, S., Metode Numerice, romania: Editura

Tehnică,1997, ISBN 973-31-1135-X
[22] Andrei T., Statistică și econometrie, Romania: Editura Economică, București, 2003. ISBN: 973-590-764-X
[23] MetaQuotes Language, 2019, – Available at: https://www.metatrader4.com/en/automated-trading/mql4-programming
[24] Brexit, The prospective withdrawal of the United Kingdom (UK) from the European Union (EU), 2016, Available at: https://en.wikipedia.org/wiki/Brexit
[25] Păuna C., TheDaxTrader automated trading system, online software presentation. 2010, Available at: https://pauna.biz/ thedaxtrader
[26] Păuna, C., Capital and Risk Management for Automated Trading Systems, Proceedings of the 17th International Conference on Informatics in Economy, May 2018, pp 183-188. Available at: https://pauna.biz/ideas