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A multi-model approach to the development of algorithmic trading systems for the Forex market

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ABSTRACT

In the decade passed, considerable affords were made to develop effective trading systems based on different assumptions concerned with the market nature, methods for data processing and uncertainty modeling. Such systems are often so sophisticated that they can be applied only by their authors. Another limitation of them is concerned with the focus on the development of a universal single best model. Besides, any model works well only in limited time periods and fails when noticeable changes in the market behavior occur. Then a major revision or the development of a new model is inevitable. Unfortunately, usually this needs too much time. Therefore, in this paper, to avoid the above problems, the simple multi-model approach to the development of trading systems in the Forex market is proposed. It is based on some working hypotheses, which are justified in this paper. The first of them is based on the observation that the Forex is the aggregation of numerous streams (strategies) provided by the broad trades community. Therefore, we can expect that even a very simple model based on the particular trading idea or ideas may catch such a string to be profitable, at least during a small period. If we have developed a set of such simple models optimized for different currency pairs, in each trading period we can use the model providing maximal profit for a certain currency pair. The profitability of the proposed approach is illustrated by the trading results obtained on the symbols EURUSD,GBPUSD, AUDUSD and USDJPY for the timeframes H1 and H4 with the use of the Meta Trader 4 platform.

1. Introduction

The foreign exchange market, known as Forex or FX, is a financial market where currencies are bought and sold simultaneously. Forex is the world's largest financial market, with a volume of more than 5 trillion. It is a decentralized market that operates 24 h a day, except for weekends, which makes it quite different from other financial markets. The characteristics of Forex show differences compared to other markets. These differences can bring advantages to Forex traders for more profitable trading opportunities. Some of these advantages include no commissions, no middlemen, no fixed lot size, low transaction costs, high liquidity, almost instantaneous transactions, low margins, high leverage, 24-h operations, no insider trading, limited regulation, and online trading opportunities. Now the Forex market is fully digitized. Thus, the development of various Expert Advisors and automated trading systems (TS), commonly referred to as algorithmic trading, is becoming a new broad branch of scientific and engineering activity.

There are several important problems associated with the development of sufficiently profitable TS. Nowadays, these systems have become extremely complex and can often only be managed by their developers. Another problem is the tendency observed in the literature to look for a single ideal trading model that provides the best results under any circumstances, but that is only a dream. Any such model can work well for some limited period, but will rest for the next one. Then a radical revision or development of a new model based on other working hypotheses becomes inevitable. Of course, this often requires too much money and time. Therefore, in the current article, in order to overcome these problems, we propose a simple multi-model approach to the development of TS for the Forex market. It is based on some general hypotheses substantiated in this article. The first of them is the assumption that Forex is a synergistic combination of numerous strategies implemented by the broad trading community and market makers. Thus, we assume that any, even a very simple model based on specific trading ideas, can implicitly follow (catch) one of these strategies and can be profitable for some small period. If we have a set of such simple models optimized for different currency pairs, in any

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given period we can use a simple model that provides maximum profit for a particular currency pair.

According to the traders' common experience, the better are the optimization results (i.e. high Profit), the lower will be result of testing (low Profit). Often in the literature, we can meet the following conclusion: If the optimized profit is large, e.g., greater than that earned by weapon traders, the results of testing, as a rule, will be very bad, and even significant losses of money often may take place. Sometimes this is called the overfitting effect. Sometimes the following statement seems to be justified enough by the trading practice: The excellent optimization results are usually accompanied by unacceptable low testing results, the good optimization leads to acceptable (at least positive Profit) testing results, and the satisfactory optimization may provide satisfactory testing results which can be used in practice. It is clear that the less-than-satisfactory optimization can bring the testing results no better than satisfactory. Therefore, the most justified recommendation for building practically useful TS, which we can find in the literature is as follows: to get acceptable testing results, long enough optimization periods should be used. It is easy to see that this recommendation is not a universal remedy for the problem at hand as it generates its own more practical problems; what does it mean "long enough optimization periods", what are the criteria to qualify optimization results as excellent, good or satisfactory. Since there are no practical recommendations in the literature concerning such criteria, the proposition to use long training period can be treated only as a part of the general methodological framework. Besides, in these times of rapidly changing market conditions, the use of long teaching periods may be undesirable because it does not allow us to react in time to significant market changes. Based on the above reasoning, on our experience and the observations of many other traders, we propose an approach that allows us to overcome the aforementioned problems to a large extent.

The general aim of this article is to develop a new simple multi-model approach to design trading systems and provide its methodological and practical justification based on real data from the Forex market. This aim is achieved by solving the relevant problems. Therefore, the main contribution of this article to solving the problems of Forex trading is the development of technical analysis methods that allow us to design a set of simplified but profitable trading models that together, within the framework of the proposed leader correction method, provide significantly more profit than any of these models individually with the same investments.

This main contribution is an aggregation of the following local contributions:

1. The general methodology based on the replace of complex "universal" trading models with sets of simple ones working well in the limited time intervals is developed. To do this, new technical analysis indicators and trading rules are introduced.
2. The methods to design profitable simple models and the corresponding problems are presented.
3. The overfitting problem is analyzed. The concepts of the positive and negative overfitting are introduced and used in the analysis.
4. The study of the selected simple models profitability and reliability based on the currency pairs EURUSD, GBPUSD, AUDUSD and USDJPY, selected as sufficiently volatile relative to the real spreads provided by the broker is carried out.
5. To implement a general approach to the trading process modeling, a multi-model simulation called "the approach based on the correction of the leader", is developed.
6. It is proved that this approach is able to offset the evidenced negative overfitting effect by the positive overfitting one with great final profits.
7. The appendices contain several complete codes of our trading support applications, ready for use on the popular MetaTrader 4 platform.

We cannot claim that this approach completely solves all the problems, but we can assume, it can alleviate their solution.

The rest of the paper is set out as follows. In Section 2, the methodological basis of the proposed approach is described as well as the new developed tools of technical analysis. The special attention is paid to the overfitting problem. Section 3 presents the process of developing a set of simple Forex trading models used in this work. The results of testing this set of models and the developed multi-model trading modeling method called the "leader correction approach" are presented in Section 4. Section 5 concludes with some comments regarding future work.

2. Background and related works

As in our recent paper Kaczmarek et al. (2022), the survey on the publications in this field up to 2020 was presented, here we will restrict ourselves by analysis of new relevant works that appeared in 2020–2023. Most of the papers were devoted to price and trend predictions accuracy without the use of results for the trading. The most interesting works are analyzed below.

In Maté and Jimeńez (2021), a promising approach to forecasting exchange rates using interval time series is proposed, unfortunately without presenting a trading system. The combination of fundamental and technical indicators is used for the forecasting the directional movement and exchange rates in the Forex market in Pornwattanavichai et al. (2022), Yıldırım et al. (2021). In the paper Hossain et al. (2022), the authors proposed a novel machine learning technique using technical analysis with a Belief Rule-Based Expert System (BRBES), and incorporating the concept of Bollinger Band to forecast stock price in the next five days. An interesting approach to design a deep network-based trade and trend analysis system is presented in Das et al. (2022). An approach to the Forex trend analysis using machine learning techniques is proposed in Sarangi et al. (2022). It is shown in Jarusek et al. (2022) that the Forex rate prediction can be improved by Elliott waves patterns based on neural networks. An incremental type-2 fuzzy classifier for stock trend prediction is developed in Shahparast et al. (2023). A useful survey of the Forex and stock price prediction using deep learning is presented by Hu et al. (2021). Obviously, we recognize the scientific significance and potential usefulness of this kind of research focused on the exchange rates predictions in the development of the Forex trading systems. At the same time, we must emphasize that without taking into account such factors as the spread, slippage, transaction costs, etc. determining the actual trading conditions, any trading strategy based only on exchange rate prediction, even if it is 100% accurate, as a rule, will be unprofitable. Therefore, in the works focusing on the development of real trading systems delivering earnings some other specific methods are usually used. In the paper Juszczuk and Kruś (2020), the technical analysis indicators are used as local fuzzified criteria in the multiple criteria based trading on the Forex market. A complete trading system with a combination of crisp trading rules on Forex time series data is developed and made available to the scientific community in Fisichella and Garolla (2021). This trading system implemented in the Meta Trader 5 trading platform is based on technical indicators derived from technical analysis. A multi-agent deep reinforcement learning framework for algorithmic trading in financial markets is presented in Shavandi and Khedmati (2022). Nevertheless, the assumptions used are in conflict with the market reality. The paper by Sadeghi et al. (2021) presents a combined technique based on an ensemble multi-class support vector machine (EmcSVM) and fuzzy NSGA-II for efficient trend classification and trading in Forex markets. At first, EmcSVM is used to forecast and classify the future market trend into uptrend, sideway, and downtrend. Then, NSGA-II is applied to optimize the hyperparameters of the proposed fuzzy trading system comprising multiple AND-OR Buy/Sell technical rules for uptrend/downtrend markets. In Zafeiriou and Kalles (2023), the assemble-based approach is used to develop the ultra-short-term trading system. In the considered case, an assemble consists of actors which are technical indicators and for that reason can be naturally treated as local criteria. Therefore, the assemble-based approaches are only non-formulated MCDM tasks hidden under modern terminology. In Roostaee and Abin (2023) the really profitable trading system is presented.

The above-mentioned multi-agent, ensemble multi-class, multi-act or, etc. approaches are actively used in different methods of machine learning in the context of trading systems development. Usually, they are based on the aggregations of models' inputs to generate the trading signal (Buy or Sell) and, therefore, they are close to a multi-modal approach in the context of the multi-objective optimization problem (Li et al., 2023; Ming et al., 2023). However, we have not found in the literature approaches based on the joint use of a network of separately optimized models in the construction of forex trading strategies. We called our method a multi-model approach realizing that similar approaches exist in other areas, so our main contribution is the development of a multi-model approach specifically to the specifics of Forex trading.

Deep learning and data clustering were used to develop an interpretable automated Forex trading model. Feature vectors were obtained from the market price index and the technical analysis indices. Data labeling was presented through clustering. A dataset was acquired to train a deep learning model to obtain the best action (Buy, $Sell$, or $Hold$). An autoencoder network was developed to avoid trading when unacceptable high fluctuations (outliers) of prices occurred. The model provides more than satisfactory trading results. It is shown in Moghaddam and Momtazi (2021) that a pattern-based approach may provide promising results in the Forex market trading. Probably the paper Peng and Lee (2021) was the first devoted to overfitting problem in the Forex trading. Overfitting in trading is the process of designing a trading system that adapts so closely to historical data that it becomes ineffective in the future. Overfitting is the usual thing in the trading system development and often is treated as a norm rather than an anomaly. The authors Peng and Lee (2021) declared that they developed the so-called log-distance path loss method, which can solve this problem. Nevertheless, this statement is not convincingly justified by them. Since the problem of overfitting is of great practical importance, we will return to it in the following. In our recent paper Kaczmarek et al. (2022), which is the continuation of the series of our works devoted to the trading system development problems (Dymova et al., 2010, 2012, 2016; Sevastianov & Dymova, 2009), we considerably extended the range of used methods for uncertainty modeling. In this paper, the application of the intuitionistic fuzzy rule-base evidential reasoning (IFRBER) to the development of a new optimized automated trading system (ATS) focused on the Forex market is presented. The used IFRBER approach is based on the treatment of the intuitionistic fuzzy sets (IFS) in the framework of the Dempster–Shafer theory, which makes it possible to avoid the revealed drawbacks of the classical A-IFS operational laws and enhance the overall performance of the IFRBER approach. Based on simple, but real-world examples, it is shown that the use of the IFRBER provides an opportunity to extract from an analyzed system considerably more useful for the decision making information than the usual fuzzy rule-base evidential reasoning (FRBER). The developed new ATS provides considerably more profitable and comfortable (with a higher percentage of winning trades and with low risks) trading than the earlier developed ATS presented in Dymova et al. (2016).

Based on the above short literature review and taking into account the last review in Dymova et al. (2016) with conclusions, we can say that currently deep learning-based approaches dominate in the stock prices and exchange rates predictions, while a critical lack of work devoted to the development of real profitable Forex trading systems is observed.

3. Preliminaries

3.1. Rationale for choosing a trading platform

To be close to the practice as possible, we should properly choose the tools for the implementation of the developed trading system. Our choice was the MetaTrader 4 platform, because its developer, MetaQuotes Software Corporation (a leader in the financial software market), had previously released a number of versions of the MetaTrader platform starting in 2002. MetaTrader 4 was a significantly enhanced version and was released in 2005. In October 2009, a significantly re-coded MetaTrader 5 went into public beta testing. The MQL4 programming language was completely revised, eventually reaching the level of MQL5. Currently, MQL4 and MQL5 use unified MetaEditor. Although MT5 was introduced in 2009, according to a study conducted in September 2019, MetaTrader 4 was still the most popular Forex trading platform in the world at the time (Forex Market Statistics, 2022). The MQL4 programming language is factually C++ language extended by numerous specific functions that greatly alleviate the designing of Expert Advancers implementing trading strategies. This is one of the reasons for the popularity of MetaTrader 4. Therefore, we will sometimes use the terminology of MetaTrader 4 and fragments of programs written in the MQL4 programming language. Most of them can be directly used in practical trading. In our studies, we used the data provided by the broker EasyForex as this firm is considered in the trader community as a reliable provider of high-quality Forex data with fixed and relatively small fixed spreads.

3.2. Terminology

To avoid possible misunderstanding, here we concretize some of the terms used in the context of Forex trading. There are different definitions of mathematical model proposed in the literature, e.g., "A mathematical model usually describes a system by a set of variables and a set of equations that establish relationships between the variables" (Wikipedia). For our purposes, we have modified this definition as follows. A trading model (hereinafter referred to as the model) is a mathematical model consisting of mathematical expressions, rules and optimized parameters that simulates the decision-making process (buying and selling decisions) during trading. The values of the optimized parameters are those that provide the maximum/minimum values of the selected criteria (profit, profit factor, relative drawdown, etc.) based on the corresponding model. Within this framework, the terms optimization, teaching, learning, training are practically synonyms. A trading system (TS) is an implementation of a model in the form of specialized software. The remaining terms in the field of the problem under consideration, necessary for a proper understanding of the article, are described in the table that makes up Appendix A (Table A.18).

3.3. Methodological justification of the proposed approach

There are several important issues related to the methodological basis of the proposed multi-model approach.

The currency exchange market is a highly stochastic and uncertain phenomenon. Therefore, in our research, we will adhere to the well-known general methodological principle: the more stochastic and uncertain is the analyzed process, the more simple should be its useful model. The next basis is the so-called inconsistency principle, which can be presented as the statement: "The real complexity of a system and the accuracy of its description are roughly inversely proportional. " The acceptance of the above principles imposes the following approach to the development of the practically applicable trading strategy.

At this stage, the simplest strategy comprising minimal necessary trading tools and only integer and real-valued parameters is designed and tested on the selected sets of currency pairs and timeframes. Only a single criterion approach, e.g., Profit maximization should be used.

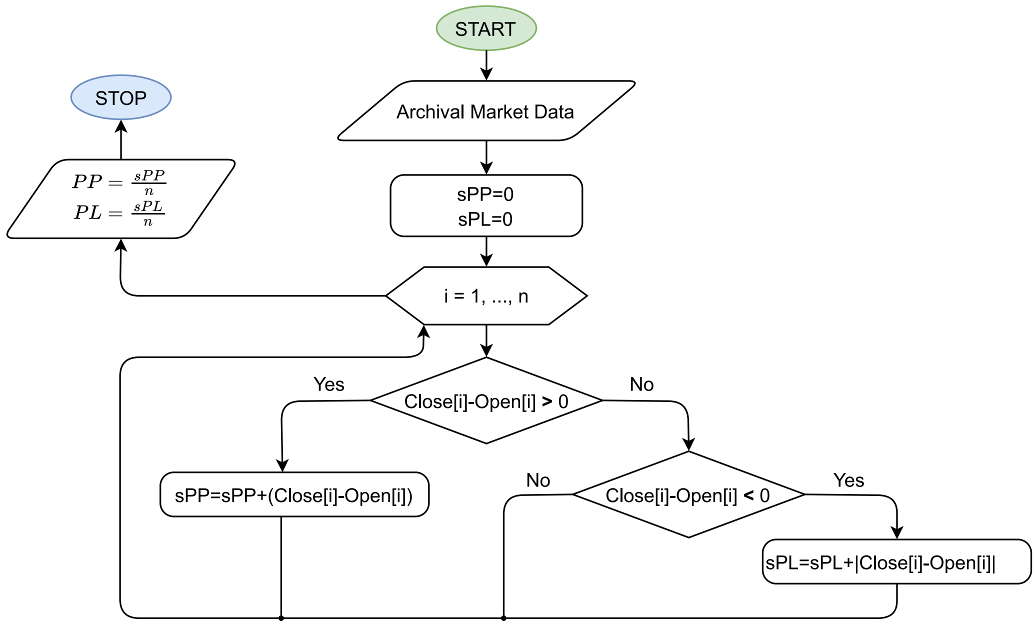

Fig. 1. Algorithm of the function CountPPPL.

At this stage, the strategy is gradually refined by including additional rules and parameters. At the beginning of this refining process, the strategy performance is enhancing until the model complexity becomes in contradiction with the real trading process uncertainty, when the strategy performance stops growing and even begins to fall with increasing model complexity. In this way, a set of simple trading models of varying complexity based on various specific trading ideas can be assembled. We can say, at this stage, we should follow the ancient Occam's wisdom: "Entities should not be multiplied unnecessarily" and the Pareto principle that states that for many outcomes, roughly 80% of consequences come from 20% of causes (the "vital few", Box & Meyer, 1986). Of course, the obtained at this stage trading models should provide acceptable, at least positive profits.

3.4. New technical analysis tools

The intersections of fast and slow Moving Average (MA) indicators are often used to generate trading signals. But it is known that, as a rule, such signals are significantly delayed. To a large extent, this is a consequence of the double processing of the source data: two MA are used. To reduce this effect, we suggest using a new $dSMA$ indicator, which is a modification of what we introduced in Kaczmarek et al. (2022). It can be calculated as follows:

$$dSMA = (Ask + Bid) * 0.5 - SMA(parm\_nn), \tag{1}$$

where SMA is the Simple Moving Average indicator ($SMA = \frac{1}{parm\_nn} \sum_{i=1}^{parm\_nn}$ Close[i]), $parm\_nn$ is its optimized period.

The drawback of the classical indicators is that most of them are based only on Close or Open prices. Also, there are several somewhat exotic indicators based on the High or Low prices. The common disadvantage of such indicators is that they are based on only one price (Open, Close, High or Low), whereas important information on the price range in the considered Bars becomes lost. Therefore, let us consider $d[i] = Close[i] - Open[i]$. Then if $d[i] > 0$ we can treat d[i] as a possible profit ($PP[i]$) else ($d[i] < 0$) we can treat $abs(d[i])$ as a possible loss ($PL[i]$). We can see that the body of the candle is taken into account and the $PP[i]$, $PL[i]$ are directly formulated in the profit–loss terms. This is attractive as our aim is the profit maximization. The averaged on the period $parm\_n$ values of PP and PL are calculated using the corresponding function (see its algorithm in Fig. 1).

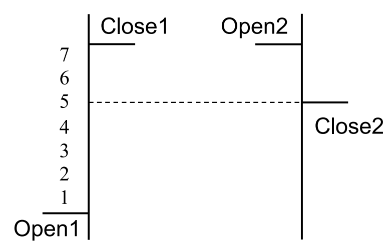

Fig. 2. The comparison of the *dSMA* and $PP - PL$ indicators in the simplest case.

The $PP - PL$ indicator works as follows: $if\ \ PP > PL$, then the possible profit on long positions is greater than on short ones, so a Buy signal is generated. Similarly, $if\ \ PP < PL$, then a Sell signal is generated.

Let us consider Fig. 2.

Since in this case $Close_2 - Close_1 = -2$, indicators based on the $Close$ prices (like $dSMA$) will generate the $Sell$ signal. On the other hand, we have $PP = 5$ and $PL = 2$. So the Buy signal will be generated. The last proposition seems to be more reasonable since the second Bar can be naturally treated as the usual correction of the trend presented by the first Bar. So we can say that the $PP - PL$ indicator is more transparent, logically justified and based on more information.

To compare the $dSMA$ and $PP - PL$ indicators using real data, we developed a simplest possible model which opens Long or Short position according to the $dSMA$ or $PP - PL$ at 8 o'clock and close it at 20 o'clock without any restrictions by the Stop Loss (SL) and the Take profit (TP) levels. To ensure this, we simply set very large unattainable values of these levels in already developed models. Fig. 3 shows the algorithm of the dSMA model and the related source code is available in Appendix B (Listing 1). However, Fig. 4 shows the algorithm of the simplest model based on the PP-PL indicator and the related source code is available in Appendix C (Listing 2).

The results obtained on optimization period 2020.09.01–2021.09.01 and testing period 2021.09.01–2022.09.01 are presented in Figs. 5–8. These figures and all subsequent ones represent MetaTrader platform reports, where Balance = Profit + Equity. In our studies, it was always assumed that Equity = $10,000.

We can see that the results of the simplest model during the testing period (Total net profit, Profit factor, Percentage of profitable

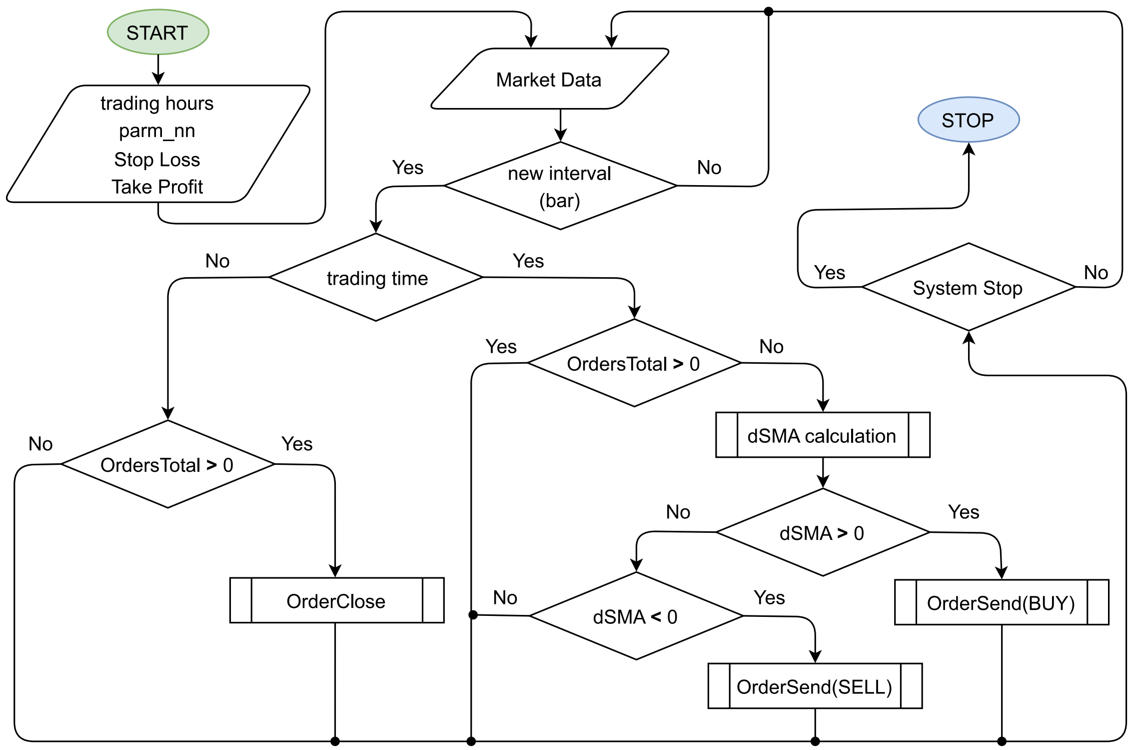

Fig. 3. SimplestModel(*dSMA*) algorithm.

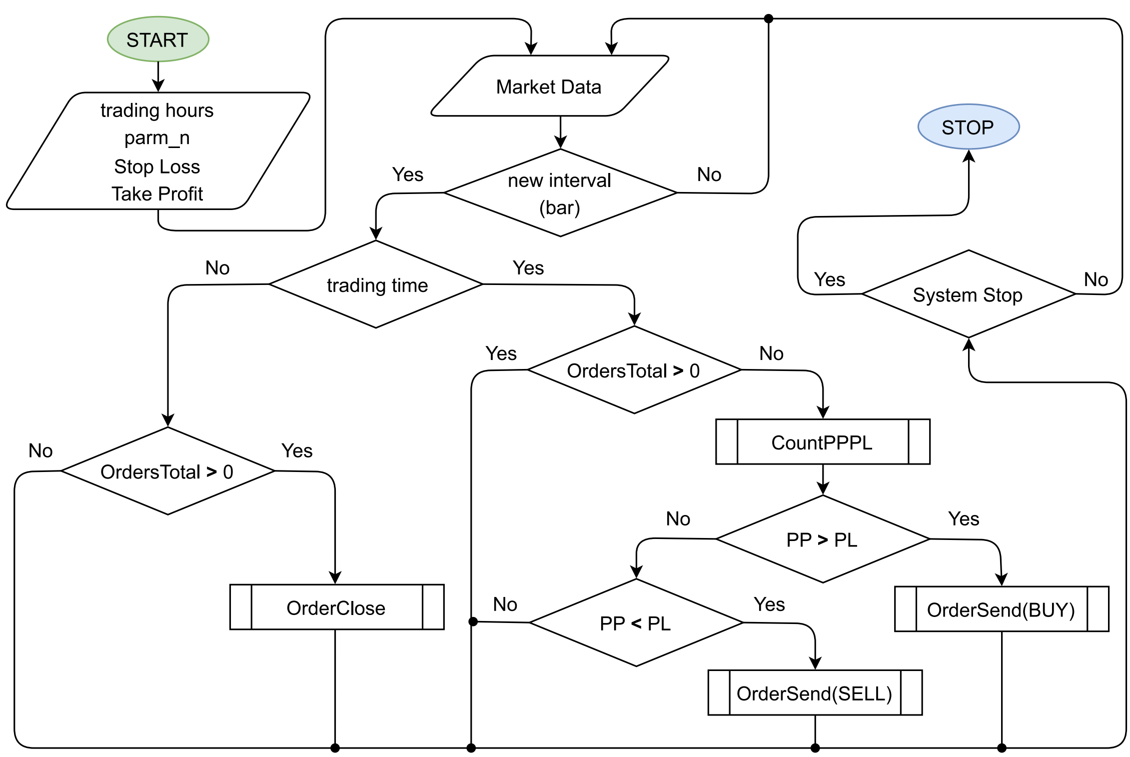

Fig. 4. SimplestModel(PP - PL) algorithm.

transactions) obtained by the use of SimplestModel(PP-PL) model are greater than the results obtained using SimplestModel(*dSMA*), while the relative drawdown is significantly less (see captions to Figs. 6 and 8).

Therefore, we can say that in the considered case the $PP - PL$ indicator performs better then $dSMA$ indicator. Somewhat surprising is the fact that both SimplestModel(*dSMA*) and SimplestModel(PP-PL) models provided significantly greater profits in the testing periods than those in the optimization period. But we will return to this phenomenon consideration in the next section in the context of the overfitting effect.

It should be emphasized that the considered simplest models with the only one optimized parameter can bring acceptable profits in the

Fig. 5. The balance curve: SimplestModel(*dSMA*), optimization period 2020.09.01–2021.09.01, EURUSD, H4. Total net profit = \$7031, Profit factor = 1.21, Relative drawdown = 30%, Total trades = 259, Profit trades = 51%.

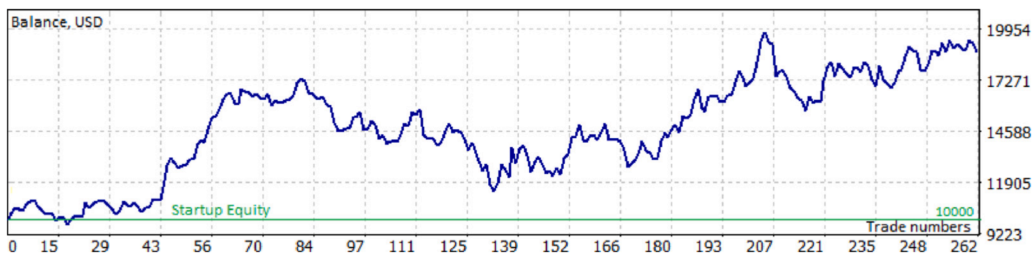

Fig. 6. The balance curve: SimplestModel(*dSMA*), testing period 2021.09.01–2022.09.01, EURUSD, H4. Total net profit = \$8760, Profit factor = 1.21, Relative drawdown = 36%, Total trades = 261, Profit trades = 36%.

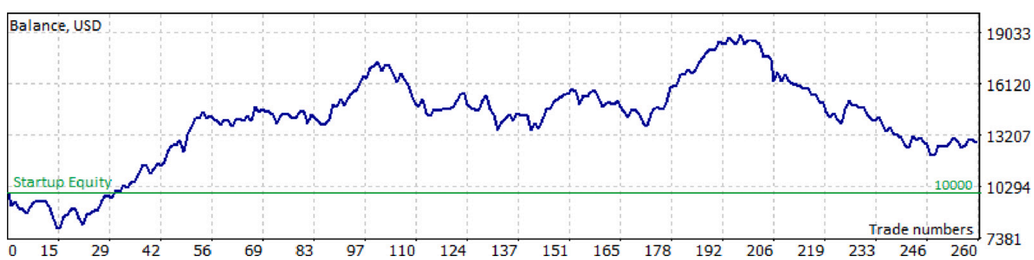

Fig. 7. The balance curve: SimplestModel(PP-PL), optimization period 2020.09.01–2021.09.01, EURUSD, H4. Total net profit = \$2771, Profit factor = 1.08, Relative drawdown = 37%, Total trades = 259, Profit trades = 48%.

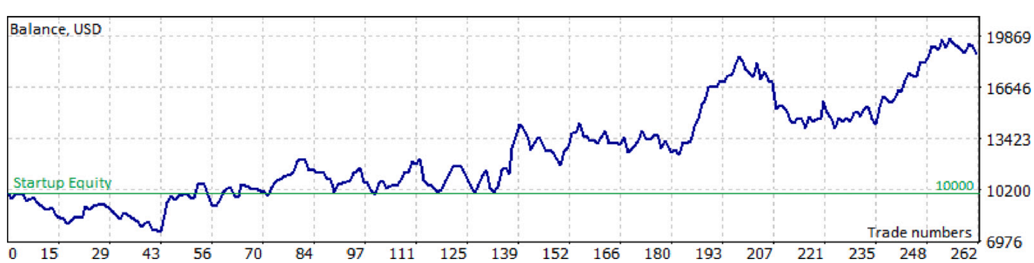

Fig. 8. The balance curve: SimplestModel(PP-PL), testing period 2021.09.01–2022.09.01, EURUSD, H4. Total net profit = \$8806, Profit factor = 1.21, Relative drawdown = 29%, Total trades = 261, Profit trades = 49%.

practical trading, at least for the particular time periods and used symbols. In Figs. 9–12, the results obtained using the comparing simplest models for the symbol USDJPY are presented.

It is seen (Figs. 10 and 12) that in the testing period, the Simplest Model(*dSMA*) model provides a small, but positive profit, while Simplest Model(PP-PL) generates a negative profit. This can serve as an indirect argument in favor of the $dSMA$ indicator, although we cannot recommend the compared indicators for real trading on the symbol USDJPY,H4, at least in the long time periods. On the other hand, the use of these models for the one or two months testing periods (see Figs. 10 and 12) may be profitable enough.

Of course, it is also possible to study the dependence of model performance on timeframes, spread, and so on. However, the result obtained suggests that the relative profitability and reliability of the $dSMA$ and $PP - PL$ indicators strongly depend on the symbol used and other factors, so it is impossible to say that one of them is better noticeable in any case. In such circumstances, the use of various aggregated indicators seems to be a promising approach.

Nevertheless, the undoubted advantage of the $PP - PL$ indicator is that, in practice, it is not affected by gaps in price quotes, since it is based on $Close[i]-Open[i]$ differences, not on $Close[i]$ prices only. Since the standard technical analysis indicators, as well as the new $dSMA$ indicator, are based only on closing prices, they are highly dependent on gaps, which can lead to incorrect trading signals. It is important that according to our studies, even a simplest model with a single optimized parameter in certain circumstances (in our case the symbol EURUSD and H4 timeframe) can provide significant profit for a long time (12

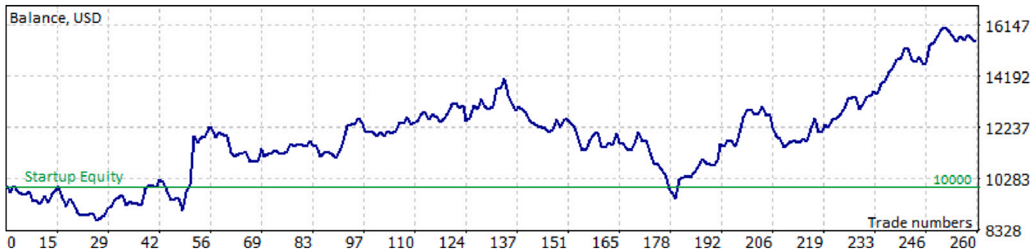

Fig. 9. The balance curve: SimplestModel(*dSMA*), optimization period 2020.09.01–2021.09.01, USDJPY, H4. Total net profit = \$5532, Profit factor = 1.23, Relative drawdown = 35%, Total trades = 259, Profit trades = 48%.

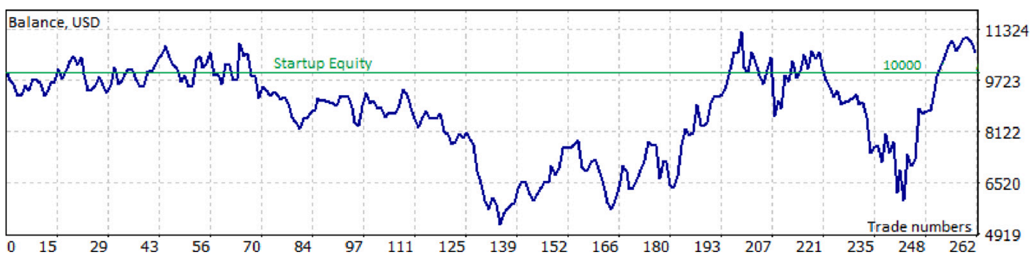

Fig. 10. The balance curve: SimplestModel(*dSMA*), testing period 2021.09.01–2022.09.01, USDJPY, H4. Total net profit = \$638, Profit factor = 1.02, Relative drawdown = 54%, Total trades = 261, Profit trades = 52%.

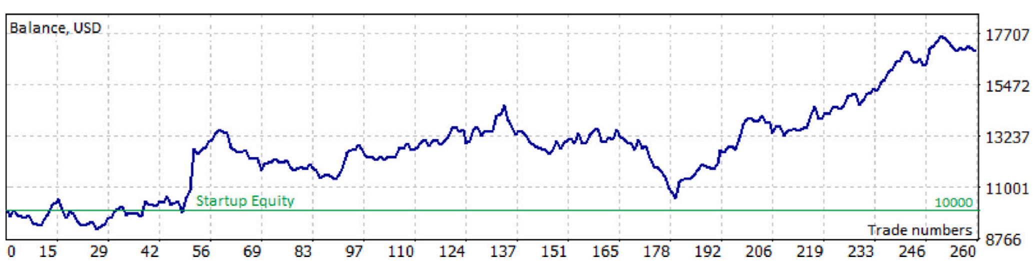

Fig. 11. The balance curve: SimplestModel(PP-PL), optimization period 2020.09.01–2021.09.01, USDJPY, H4. Total net profit = \$6950, Profit factor = 1.29, Relative drawdown = 30%, Total trades = 259, Profit trades = 54%.

months) after optimization. This is an important argument in favor of the approach we have stated.

4. Designing a set of simple forex trading models

In our recent article Kaczmarek et al. (2022), we successfully used a set of complex trading rules based on new complex indicators. Nevertheless, at this stage of research, following the principles stated in Section 3.4, we will use only the simplest $PP - PL$ and $dSMA$ indicators and their various aggregations to generate trading signals.

4.1. The trading rules and their combinations

To formulate the rules, the introduced indicators can be used solely:

$$\begin{aligned} &IF\ \ dSMA > 0\ \ THEN\ \ Buy, \\ &IF\ \ PP > PL\ \ THEN\ \ Buy, \\ &IF\ \ dSMA < 0\ \ THEN\ \ Sell, \\ &IF\ \ PP < Pl\ \ THEN\ \ Sell. \end{aligned} \tag{2}$$

A more cautious approach can be formulated as a consensus of the above atomic rules:

$$\begin{aligned} &IF\ \ dSMA > 0\ and\ PP > PL\ \ THEN\ \ Buy, \\ &IF\ \ dSMA < 0\ and\ PP < PL\ \ THEN\ \ Sell. \end{aligned} \tag{3}$$

We will call these rules "Simple Consensus Rules" (SCR). In practice, we will often meet conflicting situations like that: $dSMA > 0$ and $PP < PL$, or $dSMA < 0$ and $PP > PL$. The simplest solution is such situations is the resignation from the trading (no signal), but a more elastic approach can be used taking into account the different strengths of the atomic rules (2). In this case, the no signal can be generated as well, but only if the difference between the strengths of $dSMA < 0$ and $PP > PL$ is lesser than some minimal value ($d11$ in our application software) to be optimized. The relative strengths of $dSMA <> 0$ (dD) and $PP <> PL$ (dP) and the difference between them ($dd1$) are calculated as follows:

Based on the expression (1) we get:

$$\begin{aligned} &aa = \frac{Ask+Bid}{2}, \\ &bb = \frac{\sum_{i=1}^{parm\_nn} Close[i]}{parm\_nn}, \\ &dSMA = aa - bb, \\ &dP = \frac{|PP-PL|}{\max\{PP,PL\}}, \\ &dD = \frac{|dSMA|}{\max\{aa,bb\}}, \\ &dd1 = |dP - dD|. \end{aligned} \tag{4}$$

Fig. 12. The balance curve: SimplestModel(PP-PL), testing period 2021.09.01–2022.09.01, USDJPY, H4. Total net profit = $–873, Profit actor = 0.98, Relative drawdown = 63%, Total trades = 261, Profit trades = 51%.

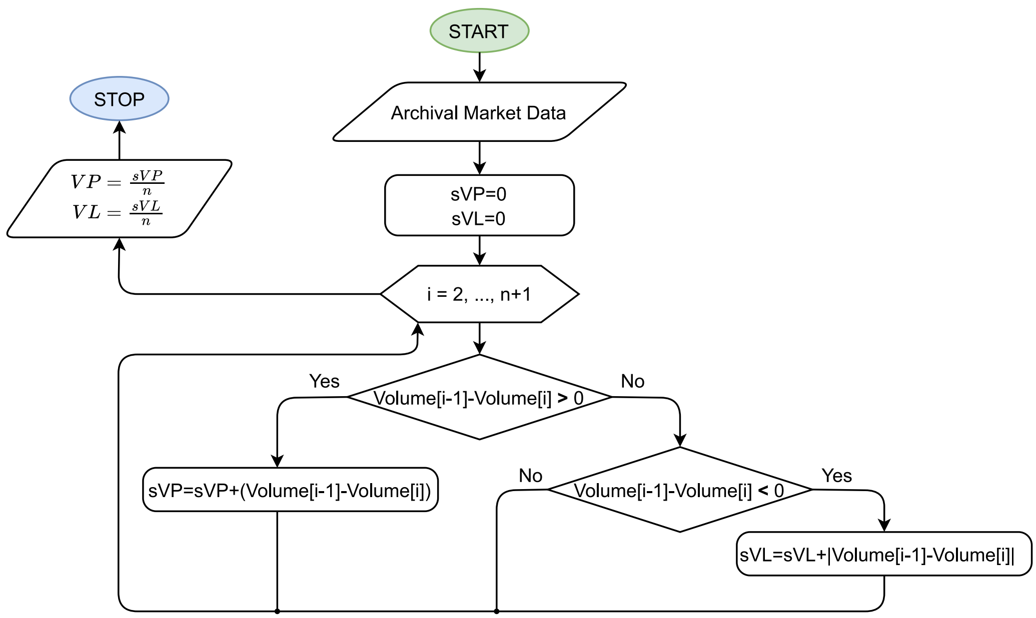

Fig. 13. Function CountVPVL algorithm.

Based on the above consideration, the set of rules that we will call "Complex Consensus Rules" (CCR) can be presented as follows:

$$IF\ \ dSMA > 0\ and\ PP > PL\ \ THEN\ \ Buy, \tag{5}$$

$$IF\ \ dSMA < 0\ and\ PP < PL\ \ THEN\ \ Sell, \tag{6}$$

$$IF\ \ dSMA > 0\ and\ PP < PL\ and\ dD > dP\ and\ dd1 > d11\ \ THEN\ \ Buy, \tag{7}$$

$$IF\ \ dSMA > 0\ and\ PP < PL\ and\ dD < dP\ and\ dd1 > d11\ \ THEN\ \ Sell, \tag{8}$$

$$IF\ \ dSMA < 0\ and\ PP > PL\ and\ dD < dP\ and\ dd1 > d11\ \ THEN\ \ Buy, \tag{9}$$

$$IF\ \ dSMA < 0\ and\ PP > PL\ and\ dD > dP\ and\ dd1 > d11\ \ THEN\ \ Sell. \tag{10}$$

Also, we introduced threshold level restrictions (TLR), which do not generate trading signals establishing opportunities for the activation of trading rules. The first of them is the power of Buy or Sell signals ($BSPower$) calculated as follows,

$$BSPower = \frac{|PP - PL|}{\max\{PP, PL\}}. \tag{11}$$

If $BSPower > d2v$ then Buy or $Sell$ signal is allowed ($d2v$ is the threshold level to be optimized). To prevent the positions opening when the volatility is too low, the parameter $ValueATR$ representing the form of the Average True Rang (ATR) was used. It was calculated as follows:

$$ValueATR = \frac{\sum_{i=1}^{ATR\_n} High[i] - Low[i]}{ATR\_n} \tag{12}$$

where ATR_n is the period of ATR to be optimized.

If $ValueATR > d\_ATR$ then Buy or $Sell$ signal is allowed (d_ATR is the threshold level to be optimized). The volumes in the Forex differ from those in the Stock market as they reflect only the number of trades made in a Bar without information of their sizes. Nevertheless, if volumes are rising in the considered period, then we can say we have rising market activity supporting the Buy or Sell decisions. Therefore, we have introduced a market activity indicator based on the differences between volumes on the neighboring Bars. This indicator is based on the parameters VP and VL representing the averaged on the last $parm\_nV$ Bars positive (VP) and negative (VL) differences $Volume[i] - Volume[i-1]$ ($parm\_nV$ is optimized parameter). This indicator called $VP - VL$ is calculated using the corresponding function, the algorithm of which is presented in Fig. 13.

It is easy to see that the relative market activity (RMA) can be calculated as follows:

$$RMA = \frac{VP - VL}{\max\{VP, VL\}}. \tag{13}$$

Then the corresponding rule is as follows. If $RMA > d3V$ then the Buy or Sell decision is allowed ($d3V$ is the optimized parameter). We can say the $BSPower$ and RMA indicators jointly support trading decisions. Besides, their values are varying in the interval [0,1] and therefore they can be treated as local criteria of relative importance $w1$ and $1 - w1$, respectively (the sum of the criteria weights should equal to 1). Therefore we have introduced the generalized criterion (GC) supporting trading decisions and the corresponding rule as follows:

$$GC = w1 * BSPower + (1 - w1) * RMA, \tag{14}$$

$$IF\ \ GC > dV4\ \ THEN\ \ the\ Buy\ or\ Sell\ decision\ is\ allowed, \tag{15}$$

where $dV4$ is the threshold parameter to be optimized.

Here we will use only weighted sum aggregation of local criteria (14), while it is shown in Dymova, Kaczmarek, Sevastjanov, and Kulawik (2021), Sevastjanov and Figat (2007) that it is not always the best choice. Besides, the local criteria can be treated as the membership functions of fuzzy subsets and the powerful mathematical tools of the fuzzy sets theory can be applied. We had used this approach in Kaczmarek et al. (2022), but here we avoid it to follow the principles stated in the previous section.

Consider the tools used to close positions. The simplest one we have introduced allows the model to close losing positions before reaching the Stop Loss level. Therefore, we call it Early Stop Loss (EST) and is calculated as

$$EST = \frac{|Close[i] - Open[i]|}{ValueATR}. \tag{16}$$

It is used as the relative strength of a price movement opposite to the open position. Suppose we are in Long and observe the local trend in the Short direction. If it is small, we can consider it as a local trend correction, but when it becomes great enough we may treat it as a trend reversal and close the position. The similar approach is used when we are in the Short position. The corresponding rule works as follows:

$$IF\ \ we\ are\ Long\ and\ Close[i] - Open[i] < 0\ and\ EST > d3\ \ THEN\ \ close\ position, \tag{17}$$

$$IF\ \ we\ are\ Short\ and\ Close[i] - Open[i] > 0\ and\ EST > d3\ \ THEN\ \ close\ position, \tag{18}$$

where $d3$ is the threshold parameter to be optimized. The main function $OrderSend$ is used in MetaQuotes 4 to open position and simultaneously establish ST and TP limits. In our applications, this function is used in the form:

$$IF\ \ Buy\ signal\ \ THEN\ \ OrderSend(open\ Long\ position;\ volume = 1.0;\ SL;\ TP), \tag{19}$$

$$IF\ \ Sell\ signal\ \ THEN\ \ OrderSend(open\ Short\ position;\ volume = 1.0;\ SL;\ TP). \tag{20}$$

We can see that in (19) and (20), the volume is equal to 1 as we used only one lot in trading. It is seen that the SL and TP levels are calculated as follows:

$$\begin{aligned} &SL = Bid - dSL, \quad TP = Ask + dTP \quad for\ the\ Long\ position,\\ &SL = Ask + dSL, \quad TP = Bid - dTP \quad for\ the\ Short\ position. \end{aligned} \tag{21}$$

The values of dSL and dTP are assumed to be dependent on the volatility. Therefore they were calculated as follows:

$$\begin{aligned} &avgHL = \frac{\sum_{i=1}^{nave} High[i] - Low[i]}{nave},\\ &dSL = avgHL * wsp\_SL,\\ &dTP = avgHL * wsp\_TP, \end{aligned} \tag{22}$$

where wsp_SL, wsp_TP and $nave$ are optimized parameters,

$$ddP = Close[i] - Open[i], \tag{23}$$

$$\begin{aligned} &IF\ \ Long\ and\ ddP > 0\ and\ ddP/Close[i] > d2\ \ THEN\\ &\quad SL = SL + ChangePoints \quad and \quad TP = TP + ChangePoints, \end{aligned} \tag{24}$$

$$\begin{aligned} &IF\ \ Short\ and\ ddP < 0\ and\ abs(ddP)/Close[i] > d2\ \ THEN\\ &\quad SL = SL - ChangePoints \quad and \quad TP = TP - ChangePoints, \end{aligned} \tag{25}$$

where $d2$ and $ChangePoints$ are optimized parameters.

Finally, the TP and ST correction is performed by the $OrderModify$ function, and the $OrderClose$ function closes open positions if necessary. In the next subsection we will show these functions in operation.

The presented set of the technical analysis indicators, thresholds and rules, some of them are first introduced in the current paper, allows us -based on their different combinations - to design a considerably broad set of simple trading models. We do not intend to describe them all, also taking into account that readers, based on the above presentation, can easily develop their own simple models. Therefore, in the future we will consider only a limited number of models, taking care mainly of their diversity.

4.2. The selected simple models

The simplest models presented in Section 1 can bring considerable profits without the SL and TP constraints. Nevertheless, in practice such trading may provide crucial losses being generally a very risky game. The SL and TP serve as a protective envelopment of trading systems, often playing an active role in trading processes. Therefore, all our models comprise the block responsible for the generation and modification of ST and TP, assuming they depend on the general volatility and local price movement. All tools required to build such a block are presented in the previous subsection. Therefore, here we present the model named Simple, which differs from the Simplest model in Section 3 only by this block in the activated form. Since this Simple model is the basic and integral part of our set of simple models, here we present the algorithm (Fig. 14) and full code of this model, in the case when the indicator $PP - PL$ is used solely, written in MQL4 and ready to use on the MT4 platform: Appendix D (Listing 3).

To illustrate the effects of the SL and TP optimization on the trading results, consider the case of the Simple(PP-PL) model with the symbol EURUSD, H4 timeframe, Optimization period 2020.09.01–2021.09.01 and Testing period 2021.09.01–2022.09.01. The results of the optimization and testing are presented in Fig. 15 and Fig. 16, respectively.

Comparing the results presented in Figs. 7 and 15, we see that the profit obtained at the optimization stage using Simple(PP-PL) is almost three times greater than that we get using SimplestModel(PP-PL). Other output parameters of the SimpleModel(PP-PL) are significantly better than those of the SimplestModel (PP-PL). Analyzing the results presented in Figs. 8 and 16, we can conclude that at the Testing stage, the results of the SimplestModel(PP-PL) are slightly better than those from the Simple Model(PP-PL) (the exception is only the Profit trades parameter).

Let us consider the case of H1 timeframe. The results obtained using SimpleModel(PP-PL) are presented in Figs. 17 and 18. We can see that in this case, all the output parameters of the SimpleModel(PP-PL) are crucially better than those we get using the SimplestModel(PP-PL) at the optimization stage, while at the testing stage we observe a completely opposite situation.

At first glance, the model provided results as in Fig. 18, cannot be used in practice, but we can see that during nearly 4 first months (until the Bar number 127) the model gradually generates the profit of about \$5000 (\$1250 in month). This is a very good result for trading by one lot. Therefore, taking into account that such situations are more a rule than an exception, in the future we will use one and two-month testing periods and a sequential re-optimization procedure called Moving Windows. It can be described as follows. Suppose, in the first step, we have the optimization period 2020.09.01–2021.09.01 (one year) and

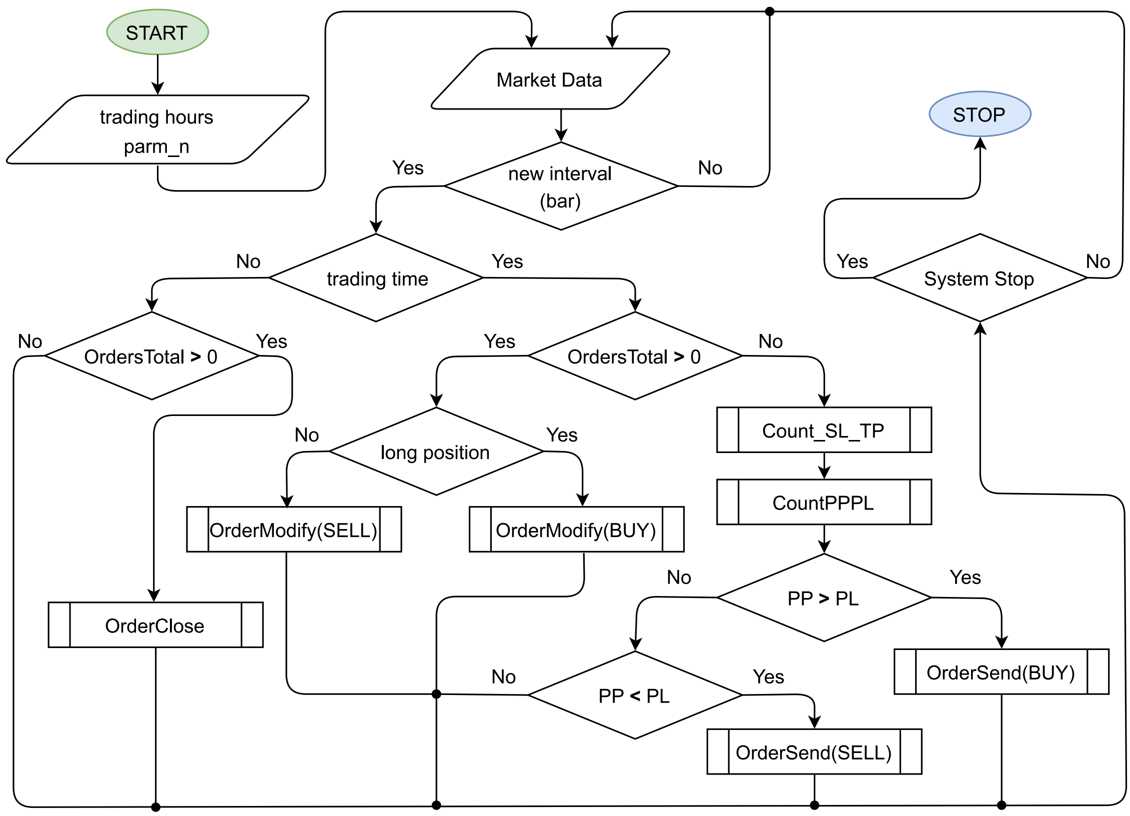

Fig. 14. Simple model(PP - PL) algorithm.

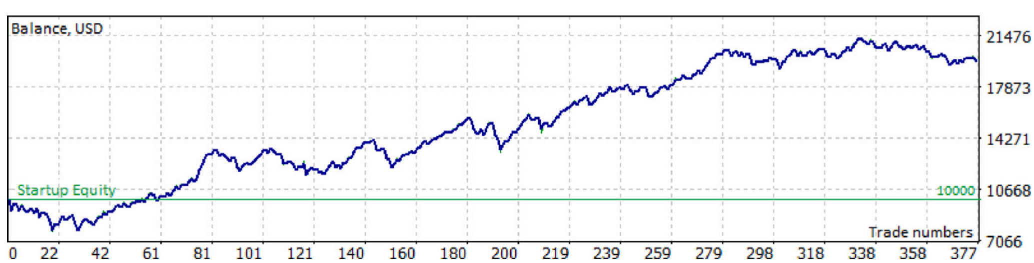

Fig. 15. The balance curve: SimpleModel(PP-PL), optimization period 2020.09.01–2021.09.01, EURUSD, H4. Total net profit = \$9686, Profit factor = 1.28, Relative drawdown = 25%, Total trades = 376, Profit trades = 57%.

Fig. 16. The balance curve: SimpleModel(PP-PL), Testing period 2021.09.01–2022.09.01, EURUSD, H4. Total net profit = \$7922, Profit factor = 1.18, Relative drawdown = 26%, Total trades = 369, Profit trades = 55%.

the testing period 2021.09.01–2021.10.01 (one month). In the second step, we will use the optimization period 2020.10.01–2021.10.01 and the testing period 2021.10.01–2021.11.01, etc.

As we showed in action 2, the rules for opening positions play a decisive role in successful trading. In Section 3, we introduced several such rules of varying complexity. Then in the spirit of our methodology, the question arises: has the complication of models reached the limit beyond which further complication is ineffective and even harmful? To check this, we have considered four models of increasing complexity, built on the basis of the rules for opening positions described in Section 3 and the basic SimpleModel.

In the first SimpleModel(*dSMA*), we used the indicator $dSMA$ as in the Eq. (2). The SimpleModel(PP-PL) is the more complex model since the $PP - PL$ indicator used as in Eq. (2) is more complex than $dSMA$.

Fig. 17. The balance curve: SimpleModel(PP-PL), optimization period 2020.09.01–2021.09.01, EURUSD, H1. Total net profit = $18,778, Profit factor = 1.55, Relative drawdown = 20%, Total trades = 395, Profit trades = 60%.

Fig. 18. The balance curve: SimpleModel(PP-PL), Testing period 2021.09.01–2022.09.01, EURUSD, H4. Total net profit = $1833, Profit factor = 1.03, Relative drawdown = 44%, Total trades = 397, Profit trades = 55%.

Table 1
The two months profits ($) obtained by compared models for 1-year optimization periods and the 2-months testing periods, EURUSD, H1.

Period	SimpleModel (*dSMA*)	SimpleModel (PP-PL)	SimpleModel (SCR)	SimpleModel (CCR)
2021.09–2021.11	−2847	−2072	−1481	−579
2021.11–2022.01	−66	−60	1624	4621
2022.01–2022.03	−1766	−2206	−460	−3227
2022.03–2022.05	3608	3730	4682	1557
2022.05–2022.07	−2544	−250	−1115	2496
2022.07–2022.09	−4105	3120	438	1655
Sum	-$7720	$2262	$4137	$6523
Profit trades	8%	17%	50%	67%

The SimpleModel(SCR) is more complex than the two last models as it is based on Simple Consensus Rules (SCR) (3) comprising both the $dSMA$ and $PP-PL$ indicators. The most complex among the proposed models is the SimpleModel (CCR) based on the Complex Consensus Rules ($CCR4$) (4)–(10).

It should be noted that the SimpleModel(*dSMA*) and the SimpleModel(PP-PL) depend on the *parm_nn* and *parm_n* optimized parameters, respectively, the SimpleModel(SCR) depends on both these parameters and the SimpleModel(CCR) additionally comprises the optimized parameter $d11$. So the complexity of the considered models is defined not only by the computation difficulty but mainly by the number of their uncertain parameters to be optimized.

The most convincing results of our studies with these models are presented in Table 1.

It is clear that we will get more reliable estimates using year profits calculated as the sum of monthly profits. Then based on the data from Table 1, we can conclude that the general model performance (year profit and Winning trades %) is strongly rising along with the model complexity increasing.

The last conclusion reflects only some general tendency, since on monthly data we can see even opposite local relations of profits. Nevertheless, based on the results of our studies (not only those presented in Table 1) we can say that the achieved level of the used models complexity is not exhausted and does not prevent further improvement of models with the use of uncertainty modeling methods, including tools of fuzzy set theory, Dempster–Shafer evidence theory, and so on. It is important that the results presented in Table 1, do not mean that we must use only the SimpleModel (CCR) since any general tendency possesses exclusions. So in practice, we can meet even the situation when the simplest SimpleModel($dSMA$) occurred to be more profitable than SimpleModel (CCR). Therefore, the current monitoring of the models used to identify the best ones, taking into account the current profitability and reliability, estimated, for example, as % of trades won to date, is the basis of our approach.

4.3. The overfitting problem

The most used definition of the overfitting effect is as follows: overfitting is "the production of an analysis that corresponds too closely or exactly to a particular set of data, and may therefore fail to fit to additional data or predict future observations reliably" (Leinweber, 2007). The different reasons for overfitting were specified. According to Tetko et al. (1995), a converted model is a model containing more parameters than can be justified by the data. This definition corresponds to the principle of inconsistency, which we discussed in Section 3.4. It is also stated in Chicco (2017) that the essence of overfitting is to have unknowingly extracted some of the residual

Fig. 19. The balance curve: SimpleModel(PP-PL), optimization period 2021.05.01–2022.05.01, EURUSD, H4. Total net profit = \$11,208, Profit factor = 1.33, Relative drawdown = 25%, Total trades = 372, Profit trades = 59%.

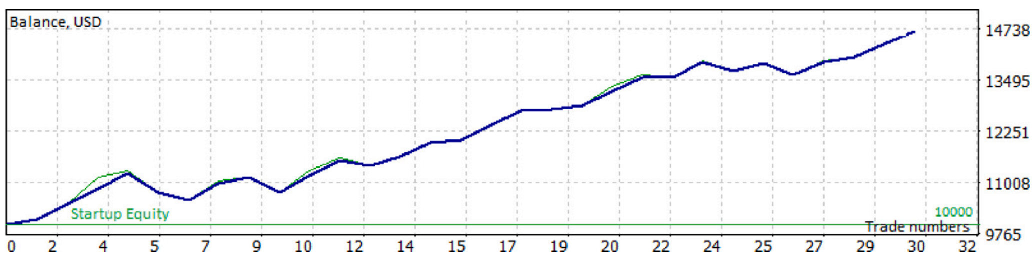

Fig. 20. The balance curve: SimpleModel(PP-PL), testing period 2022.05.01–2022.06.01, EURUSD, H4. Total net profit = \$4684, Profit factor = 3.85, Relative drawdown = 9.4%, Total trades = 30, Profit trades = 77%.

variation (i.e., the noise) as if that variation represented underlying the model structure. Therefore, the overfitting is a complex phenomenon determined by a set of causes. In the stocks and Forex markets studies, the overfitting is mainly analyzed in the context of the stocks and currencies prices prediction problem. Currently, a number of methods that allows us at least to reduce the overfitting effect in predictions are used in the financial market. For example, a group of methods comprise the addition of the $L1/L2$ regularization to the loss function (Luo et al., 2015, 2016) or noise to the original data at the optimization stage (Srivastava et al., 2014). A recent review of these methods is presented in Peng and Lee (2021), where the authors stated that the considered methods still require considerable human effort to repeatedly tune the hyperparameters. Of course, this makes the possibility of their use in practice questionable.

4.3.1. *The positive overfitting*

As we are focused on the development of the real Forex trading systems, we are interested in the direct prediction of profits obtained taking into account the spreads, slippage, transaction costs, etc., determining the actual trading conditions. This is because a trading strategy based only on exchange rates prediction, even if it is 100% accurate, as a rule, will be unprofitable. Therefore, consider the balance curve on the year optimization period (Fig. 19) 2021.05.01–2022.05.01 and on the following testing month period (Fig. 20) 2022.05.01–2022.06.01.

The total net profit for the optimization period is \$11,208, and the average monthly profit is \$934. Then the total monthly net profit for the testing period (\$4684) is five times greater than on the optimization period. Taking into account the high smoothness of the balance curve during the testing period, as well as the fact that the other important characteristics of trading during this period are several times more than during the optimization period, we can confirm the overwhelming advantage of the test period trading. Formally, in such circumstances we deal with the large overfitting, as in the case of its absence the monthly profit on the testing period should not substantially differ from the average monthly profit on the optimization one. For convenience, we will call this phenomenon the positive overfitting.

The above example is not a unique case. Let us consider Figs. 7 and 8. We can see that for the irregular balance curve in the one-year optimization period, we have a significant upward trend in the next test year period, so the annual net profit on it (\$8806) is three times greater than during the optimization period. In addition, all the important characteristics of trading during the testing period are much better than during the optimization period. We cannot explain the positive overfitting by the redundant number of model parameters as in the last example the only one optimized parameter was used. The explanation of the positive overfitting occurrence by the sudden change of the market behavior is not convincing, as we cannot see such changes in the considered example. Besides, this explanation is so universal that we can use it to explain all our failures. Thus, often we are dealing with a strong positive overfitting, but it is so desirable that we do not want to fight it.

Although we cannot now explain the nature of the positive overfitting convincingly, this does not prevent its use in practical trading. Another sudden, important and somewhat debatable conclusion is that in the spirit of above analysis, the use of the known methods for the overfitting reduction may provide undesirable results of trading, eliminating the positive overfitting.

4.3.2. *The negative overfitting*

The definition of the negative overfitting we introduce here practically coincides with those used in the traders' community. They can be cumulated in the simplest form: if, after good trading results on the optimization period, we get unacceptable results on the testing one, then we deal with the overfitting. The example of the negative overfitting is presented in Figs. 21 and 22.

When analyzing this result, we have found that the crucial for this unhappy trading is the loss of \$1750 at 16.06.2022 with the previous series of consecutive moderate losses (see Fig. 23). We can see that based on the observed downtrend the model generated justified enough Sell signal just at the beginning of power uptrend, represented by the large up candle. Such situations could be predicted using fundamental analysis. However, the quality of such predictions is very low these

Fig. 21. The balance curve: SimpleModel(PP-PL), optimization period 2021.06.01–2022.06.01, EURUSD, H4. Total net profit = $12,701, Profit factor = 1.43, Relative drawdown = 30%, Total trades = 266, Profit trades = 52%.

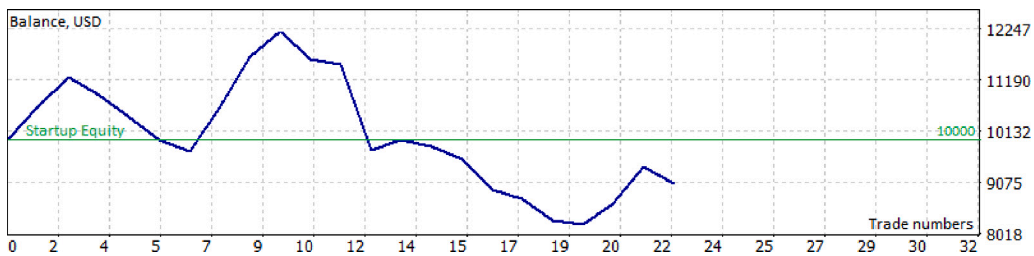

Fig. 22. The balance curve: SimpleModel(PP-PL), testing period 2022.06.01–2022.07.01, EURUSD, H4. Total net profit = -$948, Profit factor = 0.84, Relative drawdown = 36%, Total trades = 22, Profit trades = 37%.

Fig. 23. The example of unhappy trading.

days. Almost the same can be said about the effectiveness of the known methods for overfitting reduction. The only practical useful advice of experienced traders is to close active positions before the publication of important macroeconomic and political events. Unfortunately, today such a cautious tactic would leave too little time for trading itself.

4.3.3. Is it possible to reduce the negative overfitting?

In the Forex trading devoted articles, we often meet the following "practical advice". First find the optimal solution based on the profit maximization. The if on the testing period a practically useful result is obtained, we can say the problem is solved and the overfitting problem is overcome.

In the opposite case, the seemingly obvious reasoning is used: the overfitting is associated with the too great optimal profits. i.e., to overfit means to overteach the model to provide great profits on the optimization period. Therefore, we should find some suboptimal solution with a lower optimal profit providing acceptable results on the testing period. Sometimes this brings good results and the MetaTrader 4 involves the tools helping to do this manually.

For example, after optimization, MetaTrader 4 generates a table whose rows contain the parameters of a large number of non-optimal solutions placed from the solution with the highest profit ($max\ \ Profit_{opt\_test}$) to the solution with the lowest profit ($min\ Profit_{opt\_test}$). Then it is not difficult to establish the middle solution and two additional intermediate ones. As a result, we get 5 columns in Table 2 representing monthly profits on the testing periods. In Table 2, $Profit_{opt\_test}$ is the suboptimal profit on the year optimization period, $Profit_{test}$ is the monthly profit on the corresponding testing period.

We can see that Sum max $Profit\_test$ ($9175) is 24 times greater than Sum middle $Profit\_test$ ($385), although in particular months the considerable $Profit\_test$ are observed. Moreover, the maximal monthly profit ($4850) was obtained on the period 2022.05.01–2022.06.01 for the middle $Profit_{opt\_test}$. The Sum min $Profit\_test$ is negative, but not in all months. In the considered case, even the primitive statistics (sum, average) is in contradiction with the common sense of the traders' community. Nevertheless, only statistical-based results should be taken into account in the so diverse phenomenon as the Forex market. Therefore, our practical recommendation is to use only optimized solutions with

Table 2
The suboptimal results for SimpleModel(PP-PL), EURUSD, H4, year optimal and month testing periods.

Period (start–end)		*min*		*middle*		*max*
2021.09 (2021.09.01–2021.10.01)	$Profit_{opt\_test}$	3053	3938	5003	7483	10243
	$Profit_{test}$	−191	419	−1253	1145	555
2021.10 (2021.10.01–2021.11.01)	$Profit_{opt\_test}$	3084	4556	6060	10521	12211
	$Profit_{test}$	−729	−1135	−939	1658	432
2021.11 (2021.11.01–2021.12.01)	$Profit_{opt\_test}$	3006	5006	5499	9426	10899
	$Profit_{otest}$	1719	1938	1087	2411	2061
2021.12 (2021.12.01–2022.01.01)	$Profit_{opt\_test}$	2993	4524	6113	9022	12248
	$Profit_{test}$	−3345	−4762	−1187	−2262	−2401
2022.01 (2022.01.01–2022.02.01)	$Profit_{opt\_test}$	3104	4229	5489	8152	11101
	$Profit_{test}$	597	335	1427	1246	1812
2022.02 (2022.02.01–2022.03.01)	$Profit_{opt\_test}$	3085	4567	6232	9044	12465
	$Profit_{test}$	−751	−1649	−586	−1858	−2547
2022.03 (2022.03.01–2022.04.01)	$Profit_{opt\_test}$	3021	3290	4408	8498	9722
	$Profit_{test}$	1721	2929	−525	990	775
2022.04 (2022.04.01–2022.05.01)	$Profit_{opt\_test}$	3060	3506	5085	7541	10442
	$Profit_{test}$	−531	1546	−130	−1246	331
2022.05 (2022.05.01–2022.06.01)	$Profit_{opt\_test}$	3042	4255	5643	8078	11387
	$Profit_{test}$	2982	3430	4850	4116	4673
2022.06 (2022.06.01–2022.07.01)	$Profit_{opt\_test}$	3006	4561	6461	9644	13049
	$Profit_{test}$	−3868	−3448	−3679	−1337	−948
2022.07 (2022.07.01–2022.08.01)	$Profit_{opt\_test}$	3013	4772	6497	9654	13044
	$Profit_{test}$	−1618	−2008	1327	735	892
2022.08 (2022.08.01–2022.09.01)	$Profit_{opt\_test}$	3145	5146	7176	10524	14355
	$Profit_{test}$	742	544	−6	−381	3541
	Sum	−1322		385		9175

maximum profit, without considering suboptimal solutions. In addition, we do not advise rushing with the use of known methods of combating the overfitting, since they do not take into account and apparently destroy the positive overfitting effect identified in this work, which often plays a decisive role in the formation of profit.

5. The results of studies

The presentation of our approach is based on the empirical basis obtained on four currency pairs: EURUSD, GBPUSD, AUDUSD and USDJPY, selected as sufficiently volatile relative to the real spreads provided by the broker. We used the H4 timeframe because the four-hour candle represents half of each geographic trading session. Each of these sessions can take on markedly different tones, and that is where traders can look for potential opportunities. Also, we used the H1 timeframe as the most popular in algorithmic trading. We applied the Moving Windows approach with one year optimization period and one or two months duration of testing periods. We used the data in the period 01.09.2021–31.08.2022 from the EasyForex broker providing high-quality forex data with fixed and relatively small spreads.

In Sections 5.1–5.4, we have presented the results of testing our models on a sample for 12 months (1 year). According to our experience and the general opinion of the broad trader community, such a sample is sufficient to assess the quality of the model if we are dealing with intraday trading (in our case on the 1H and 4H timeframes). In any case, such a sampling duration allows us to select promising models with appropriate timeframes and currency pairs for use in a multi-model trading algorithm. However, in Section 5.5, where we present our multi-model approach, in order to be sure of the results obtained, we used a sample almost twice as long (about 2 years). Our research was based on intraday trading with an active time from 08 to 20 h for the H4 timeframe and from 09 to 21 h for the H1 timeframe. According to our preliminary research, these time intervals are the most profitable. In all cases, the position size was equal to 1 lot with the leverage 1:100. The models we have selected for the developed approach presentation are of different complexity, some of them are based on different ideas concerned with the Forex market behavior. To achieve greater diversity, which is a necessary component of our approach, we used different sets of models working on different timeframes for selected currency pairs.

5.1. The EURUSD currency pair

In this case, we consider three models of different complexity, two of them, the SimpleModel (SCR) and SimpleModel (CCR) are described in Section 4.2. The third model (SimpleModel ($SCRGC$)) was designed as the Simple model based on the Simple Consensus Rules, supported by the generalized criterion (GC) of market activity (14). In Tables 3 and 4, the names of these models are abbreviated as $SM(SCR)$, $SM(SCRGC)$ and $SM(CCR)$.

Let us analyze Tables 3 and 4.

The results obtained using H1 timeframe generally are acceptable but considerably worst than those we get with the use of H4. The greatest year profit (Sum) is provided by $SM(SCR)$, H4, the close results brought the $SM(CCR)$, H4 on one-month testing periods. The year profits obtained on the two-months testing periods are lesser, but their accuracy ($\%\ Winning\ Trades$) is greater than that for one-month testing periods.

5.2. The GBPUSD currency pair

In this case, we used the described above models $SM(SC)$, $SM(SERGS)$ and the model based on the Complex Consensus Rules (CCR). Additionally, this model closes positions when the relative strength of a price movement, opposite to the open position (EST) presented by Eq. (16), becomes great enough and then immediately opens the opposite position. So we deal with the trend reversal model of moderate complexity we call $SM(CCRR)$. Such a model can be helpful in the case of the greatly volatile, fast-changing currency pair GBPUSD.

In Figs. 24 and 25 we see that although for the optimization period we obtained acceptable result, for the testing period only for six first months the current profits are positive. Hence, the use of the Moving Windows strategy is necessary.

In Tables 5 and 6, we can see that the SM(SCR) and SM($SERGS$) models failed practically in all cases, whereas the model MM($CCRR$) provided good year results for one-month testing periods that can be used in practice. The best results were obtained for the two-month testing period and H4 timeframe. All this confirms our hypothesis about the expediency of using models that include fast trend-reversal processes in the development of trading strategies on the pair GBPUSD.

Table 3
Month profits on one-month testing periods.

Period	$SM(SCR)$ H4	$SM(SCRGC)$ H4	$SM(CCR)$ H4	$SM(SCR)$ H1	$SM(SCRGC)$ H1	$SM(CCR)$ H1
2021.09	1194	−259	−444	−328	−298	780
2021.10	384	287	1458	−130	2267	−659
2021.11	2352	1934	2161	1400	2060	2281
2021.12	800	−1840	−2162	−206	−1029	1517
2022.01	1619	−230	825	2414	2240	919
2022.02	−2436	−2030	−1734	−5039	−3734	−3167
2022.03	1555	3260	3539	1719	717	696
2022.04	168	−158	150	−974	−632	975
2022.05	4677	2547	3372	3336	3590	5510
2022.06	−1932	−4498	−1959	−2740	−3025	−1674
2022.07	1465	290	671	2556	2115	1527
2022.08	1901	1891	3642	3073	2173	−995
Sum	11750	1192	9519	8142	7334	7710
Month average	979	99	794	680	612	642
Winning trades	83%	50%	67%	50%	58%	67%

Table 4
Two-month profits on two-month testing periods.

Period	$SM(SCR)$ H4	$SM(SCRGC)$ H4	$SM(CCR)$ H4	$SM(SCR)$ H1	$SM(SCRGC)$ H1	$SM(CCR)$ H1
2021.09–2021.10	390	209	1603	−1481	−419	−503
2021.11–2021.12	590	1092	−299	1624	2959	795
2022.01–2022.02	−552	−2742	−906	−460	−3361	−1126
2022.03–2022.04	347	5346	3210	4682	382	1694
2022.05–2022.06	3566	879	1878	−1115	2862	724
2022.07–2022.08	1798	1018	2743	438	3136	1822
Sum	6173	5802	8226	4137	5559	3406
Month average	511	483	686	344	463	284
Winning trades	83%	83%	67%	50%	67%	67%

Fig. 24. The balance curve: SimpleModel(SCR), optimization period 2020.09.01–2021.09.01, GBPUSD, H4. Total net profit = \$12,912, Profit factor = 1.19, Relative drawdown = 28%, Total trades = 519, Profit trades = 55%.

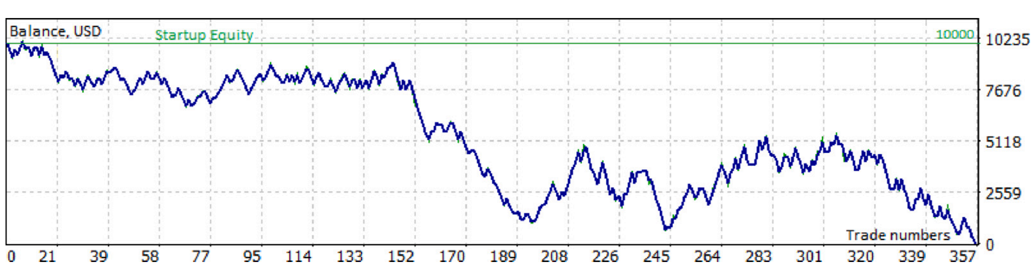

Fig. 25. The balance curve: SimpleModel(SCR), testing period 2021.09.01–2022.09.01, GBPUSD, H4. Total net profit = -\$9954, Profit factor = 0.84, Relative drawdown = 99%, Total trades = 356, Profit trades = 47%.

5.3. The AUDUSD currency pair

When looking at Figs. 26 and 27 we can conclude that in this case, the need to use the Moving Window approach is obvious.

In Tables 7–9, the $SM(PP-PL)$ is the Simple model based on the $PP-PL$ indicator solely, the $SM(PP-PL,GC)$ is the simple model based on the $PP-PL$ indicator supported by the general criterion GC (see Eq. (14)), the $SM(CCRGC)$ is the simple model based on the complex consensus rules CCR, supported by the general criterion GC. The other models were described above.

We can see that the best result with a year profit of \$7389, the won trades 58% and one-month testing period was obtained using the

Table 5
Month profits on one-month testing periods.

Period	$SM(SCR)$ H4	$SM(SERGC)$ H4	$SM(CCRR)$ H4	$SM(SCR)$ H1	$SM(SERGS)$ H1	$SM(CCRR)$ H1
2021.09	2647	1015	4722	6018	3547	4149
2021.10	−1496	−1432	−817	2266	968	1406
2021.11	−356	3518	3393	−712	150	1180
2021.12	−2800	−3931	−4928	−2531	−2050	−2180
2022.01	−630	−2838	1910	−3790	−4607	−2237
2022.02	214	−303	696	−2669	−2197	282
2022.03	−2721	−2643	−1274	−3227	−1620	−4290
2022.04	1315	1269	580	−529	−489	−107
2022.05	774	−2205	−573	−1321	−3121	−4284
2022.06	−623	426	4822	9429	8292	8542
2022.07	−1837	−3836	−215	1553	1553	1659
2022.08	−904	−1613	−4072	−2604	−2020	433
Sum	−6201	−12881	4309	562	−12881	4554
Month average	−508	−1073	359	47	−1073	379
Winning trades	33%	33%	50%	33%	33%	58%

Table 6
Two-month profits on two-month testing periods.

Period	$SM(SCR)$ H4	$SM(SERGC)$ H4	$SM(CCRR)$ H4	$SM(SCR)$ H1	$SM(SERGS)$ H1	$SM(CCRR)$ H1
2021.09–2021.10	1973	656	2774	9273	2233	2502
2021.11–2021.12	−654	334	−221	603	−1326	−448
2022.01–2022.02	843	−1012	3110	−2860	−4036	1183
2022.03–2022.04	−5285	−3749	461	−1464	−3423	1929
2022.05–2022.06	2901	5303	3473	−2123	−2144	−4179
2022.07–2022.08	−5613	−6368	−3676	−4946	−4985	−6566
Sum	−5835	−4835	5885	−1540	−13681	−5579
Month average	−486	−403	490	−128	−1140	−465
Winning trades	50%	50%	67%	33%	17%	50%

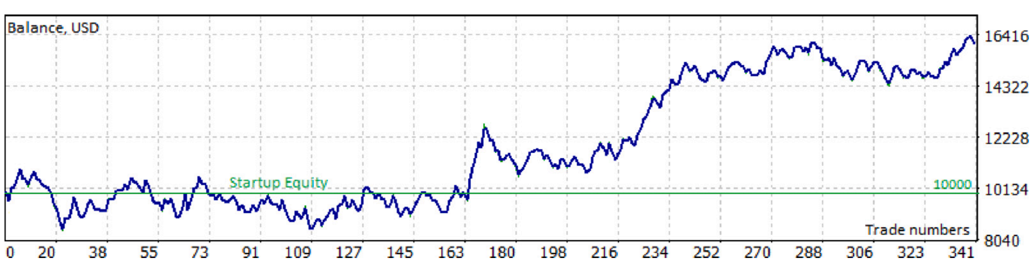

Fig. 26. The balance curve: SimpleModel(PP-PL), optimization period 2020.09.01–2021.09.01, AUDUSD, H4. Total net profit = $6072, Profit factor = 1.18, Relative drawdown = 25%, Total trades = 340, Profit trades = 51%.

Fig. 27. The balance curve: SimpleModel(PP-PL), testing period 2021.09.01–2022.09.01, AUDUSD, H4. Total net profit = -$222, Profit factor = 1.01, Relative drawdown = 36%, Total trades = 340, Profit trades = 49%.

$SM(PP-PL,GC)$ model on the H4 timeframe, whereas for the two month testing periods the best result with a year profit of $7321, the won trades 67% was obtained by the model $SM(PP-PL)$ on the H4 timeframe. Both these results are good enough to be used in practice.

5.4. The USDJPY currency pair

In Figs. 28 and 29, we can see that although the Moving Windows procedure should be applied, during the first two months of the testing periods we obtained positive profits. Therefore we can hope to get good results using two-month testing periods.

When analyzing the results presented in Tables 10–12, we can see that the maximal year profit obtained on one-month testing periods and H1 timeframe is considerable greater than that we got using the H4 timeframe.

When analyzing the results presented in Tables 10–12, we can see that the maximal year profit obtained on one-month testing periods and the H1 timeframe is considerable greater than that we got using

Table 7
Month profits on one-month testing periods for H4 timeframe.

Period	$SM(PP-PL)$	$SM(PP-PL,GC)$	$SM(CCR)$	$SM(CCRGC)$	$SM(CCRR)$
2021.09	407	281	1167	1192	845
2021.10	−1527	−852	−1572	−1348	−2154
2021.11	−817	−1594	−794	−597	−1149
2021.12	692	2155	1682	1682	1682
2022.01	1528	2884	893	709	893
2022.02	1013	587	413	675	149
2022.03	−907	−347	−3393	−3393	−3593
2022.04	−1392	−2186	−1170	−1050	−1374
2022.05	2455	2581	2000	2063	2502
2022.06	743	2213	−819	−1112	−500
2022.07	−2747	−1410	−2917	−2720	−2927
2022.08	2323	3068	2345	2302	2045
Sum	2778	7380	−2165	−1293	−3581
Month average	231	615	−180	−108	−298
Winning trades	58%	58%	50%	50%	50%

Table 8
Month profits on one-month testing periods for H1 timeframe.

Period	$SM(PP-PL)$	$SM(PP-PL,GC)$	$SM(CCR)$	$SM(CCRGC)$	$SM(CCRR)$
2021.09	1906	2062	570	570	570
2021.10	−2238	−2490	−1417	−1761	−1428
2021.11	−1641	−779	−2548	−2516	−2516
2021.12	−2063	−172	79	995	702
2022.01	−2886	743	1119	3150	3069
2022.02	−2630	−883	−827	−429	−289
2022.03	−190	1450	−1333	−1951	−2163
2022.04	−765	−1909	−1800	−1702	−1702
2022.05	489	330	1293	2473	1331
2022.06	734	1882	2793	1909	1252
2022.07	−1741	−3278	−2620	−1845	−1362
2022.08	2443	−2125	2080	2080	2080
Sum	−8582	−5169	−2611	4543	718
Month average	−717	−430	−217	379	60
Winning trades	33%	42%	50%	50%	50%

Table 9
Two month profits on two-month testing periods.

Period	$SM(PP-PL)$ H4	$SM(PP-PL,GC)$ H4	$SM(CCRGC)$ H4	$SM(PP-PL)$ H1	$SM(PP-PL,GC)$ H1	$SM(CCRGC)$ H1
2021.09–2021.10	−1725	592	−362	371	−20	−1385
2021.11–2021.12	1084	−1133	11	−1599	−2473	−1538
2022.01–2022.02	3664	2196	1024	−361	−2201	−1948
2022.03–2022.04	−725	−1795	−5867	−1040	−435	−2321
2022.05–2022.06	4619	4877	3008	3223	1225	2444
2022.07–2022.08	404	−193	−1043	200	−4263	−429
Sum	7321	4544	−3230	795	−6167	−5177
Month average	610	379	−269	66	−514	−431
Winning trades	67%	50%	50%	50%	17%	17%

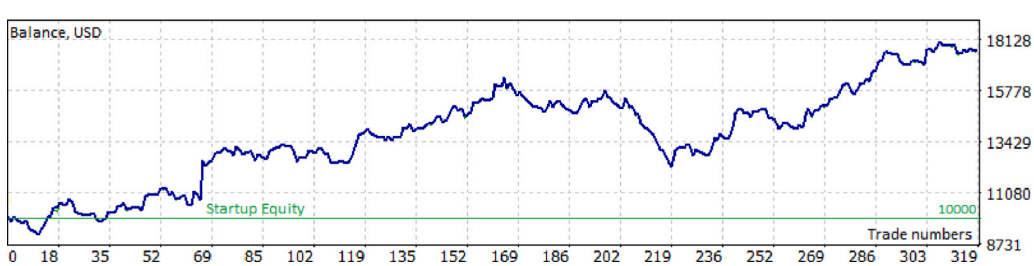

Fig. 28. The balance curve: SimpleModel(PP-PL), optimization period 2020.09.01–2021.09.01, USDJPY, H4. Total net profit = \$7603, Profit factor = 1.33, Relative drawdown = 26%, Total trades = 318 Profit trades = 47%.

the H4 timeframe. On the other hand, the profit we got in the first case (\$8158) is a bit greater than that we obtained using two-months testing periods and the H4 timeframe (\$8081), whereas the accuracy (% Winning Trades) in the last case (67%) is considerably greater of that in the first case (58%). Therefore, to choose properly the model, testing period and the timeframe, in the considered case, we should solve the two-criteria decision-making problem, but this is out of the scope of this paper.

A natural question arises how to evaluate the quality of new models? Usually a comparison with the results of previously developed models is used. We have been tracking Forex literature for the past two decades and we can say that the vast majority of publications were

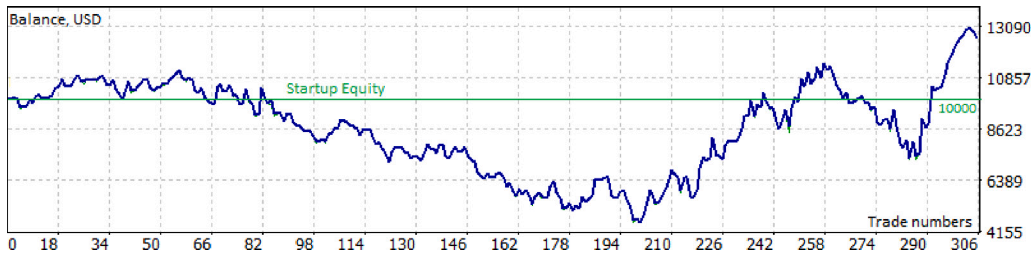

Fig. 29. The balance curve: SimpleModel(PP-PL), testing period 2021.09.01–2022.09.01, USDJPY, H4. Total net profit = \$2592, Profit factor = 1.07, Relative drawdown = 60%, Total trades = 305 Profit trades = 49%.

Table 10
Monthly profits on one-month testing periods for H4 timeframe.

Period	$SM(PP-PL)$	$SM(SCR)$	$SM(PP-PL,GC)$	$SM(CCRGC)$	$SM(CCR)$	$SM(CCRGC)$	$SM(CCRR)$
2021.09	2856	665	−8	9	−323	−323	−323
2021.10	657	189	342	1308	778	778	778
2021.11	−659	−753	−521	159	−100	−100	−100
2021.12	−1254	−998	−1635	−1598	−949	−949	−949
2022.01	1647	1374	−1264	1075	1287	1869	1635
2022.02	−1056	−1214	−1417	−1175	−1503	−1503	−1572
2022.03	−620	257	20	886	405	730	404
2022.04	320	−1804	545	266	−1293	−1284	−1293
2022.05	−875	993	−488	3091	1574	1872	679
2022.06	5078	3428	2914	2814	4100	3042	3963
2022.07	−110	823	−3218	−792	−162	−806	−272
2022.08	−267	−4770	−1116	−1728	−4081	−4827	−3541
Sum	5717	−1824	−5746	4314	−267	−1501	−591
Month average	476	−152	−487	360	−22	−125	−49
Winning trades	42%	58%	33%	67%	42%	42%	42%

Table 11
Month profits on one-month testing periods for H1 timeframe.

Period	$SM(PP-PL)$	$SM(SCR)$	$SM(PP-PL,GC)$	$SM(CCRGC)$	$SM(CCR)$	$SM(CCRGC)$	$SM(CCRR)$
2021.09	1789	190	314	818	471	1314	−403
2021.10	−409	690	1010	−528	−176	−1292	−210
2021.11	−315	918	−320	1225	−565	−1277	−1222
2021.12	−2447	−1938	−837	−649	−643	−644	−370
2022.01	−371	−1182	413	84	1650	86	1699
2022.02	−1124	730	−1575	−834	−2426	−2848	−2426
2022.03	1919	−130	832	−969	2486	2486	2216
2022.04	−1748	−528	−525	−697	−1644	−1644	−1644
2022.05	256	397	−111	−146	794	596	596
2022.06	7268	1680	6644	5277	2937	2937	2937
2022.07	591	10	1004	−556	−924	−924	−1032
2022.08	−3027	−3799	1000	−742	−3420	−3496	−2398
Sum	2394	−2963	8158	−2283	−1003	−4705	−41
Month average	200	−245	580	190	−84	−392	−3.4
Winning trades	42%	58%	58%	33%	33%	42%	33%

Table 12
Two-month profits on two-month testing periods.

Period	$SM(PP-PL)$ H4	$SM(PP-PL,GC)$ H4	$SM(CCRR)$ H4	$SM(PP-PL)$ H1	$SM(PP-PL,GC)$ H1	$SM(CCRR)$ H1
2021.09–2021.10	1681	2404	467	1478	2460	1441
2021.11–2021.12	−537	−909	−2951	−2126	−533	−314
2022.01–2022.02	226	645	628	−1883	−521	−923
2022.03–2022.04	−1631	−124	−1312	1094	1322	479
2022.05–2022.06	5349	5868	3777	4419	973	5991
2022.07–2022.08	394	197	−4145	−3572	−4562	−5173
Sum	5482	8081	−3536	−590	−861	1501
Month average	457	673	−295	−49	−72	125
Winning trades	67%	67%	50%	50%	50%	50%

devoted to exchange rate forecasting and only very few papers dealt with the problems of building real trading systems. Among them, we found only one work Fisichella and Garolla (2021) (abbreviated here as $F\&G$) whose results were obtained in conditions close to ours and therefore partially suitable for comparison with ours. They presented the annual profits for the whole of 2019, 2020 and the first four months of 2021, obtained using their model. Table 13 shows a comparison of their results with ours and the BSH strategy. Since the leverage of 1:30 was used in $F\&G$, our results in Table 13 were obtained based on the same leverage. To make the comparison more convincing, we used only

Table 13
The comparison of $SM(PP-PL)$ and $F\&G$ models results.

Date	Model		EURUSD		GBPUSD		USDJPY	
			H1	H4	H1	H4	H1	H4
2019 (01.01. –31.12.)	$SM(PP-PL)$	Profit	1384	1714	5365	3369	1083	565
		Total trades	451	286	449	306	422	275
	F & G	Profit	2113	3470	386	1491	−647	−176
		Total trades	59	46	150	74	68	51
	BSH	Profit	501		791		401	
2020 (01.01. - 31.12.)	$SM(PP-PL)$	Profit	2121	4156	3542	3678	3380	2231
		Total trades	475	289	485	286	417	286
	F & G	Profit	195	884	−718	3884	621	1552
		Total trades	138	78	213	102	89	66
	BSH	Profit	1838		0		0	
2021 (01.01. - 30.04.)	$SM(PP-PL)$	Profit	1042	1055	1277	352	1004	1455
		Total trades	129	95	152	90	163	92
	F & G	Profit	−391	−715	1717	−49	109	2301
		Total trades	27	21	55	27	22	13
	BSH	Profit	517		260		1622	
All Total	$SM(PP-PL)$	Profit	4547	6925	10184	7399	5467	4251
		Total trades	1055	670	1086	682	1002	653
	F & G	Profit	1917	3639	1385	5326	83	3677
		Total trades	224	145	418	203	179	130
	BSH	Profit	2856		1051		2023	

the results of our simplest and, therefore, not the most profitable model $SM(PP-PL)$, the full code of which is given in the Appendix.

There are 24 cases of the models comparison presented in Table 13 (zero values of the results of the BSH strategy mean that only negative profit was received, regardless of the type of open position (Long or Short)). In 19 of them, the model $SM(PP-PL)$ provides a larger annual profit than that obtained using the $F\&G$ model. The $SM(PP-PL)$ model provides only positive profits, while the $F\&G$ model generates annual negative profits in 6 cases. The annual profits generated by the $SM(PP-PL)$ model are greater than when using the BSH strategy, while the $F\&G$ model in 6 cases gives results less than when using the BSH strategy. The generalized results (from 01.01.2019 to 30.04.2021) obtained using the $SM(PP-PL)$ model are 1.5–5 times higher than the results obtained using the $F\&G$ model. Therefore we can conclude that our simplest model $SM(PP-PL)$ seems to be considerably more profitable and reliable than the $F\&G$ one.

Nevertheless, we are not going to claim that we have developed some better ideal models because this is not the purpose of our article but we can confidently assert that our models are no worse than others. This is quite enough for us, since the goal is to prove the superiority of our multi-model approach in which the requirements for the quality of particular models can be very simplified.

5.5. Multi-model simulation modeling of the trading process (an approach based on leader correcting (ALC))

To alleviate the presentation, we introduced the object we call Trading Tool (TT) consisting of the three components as follows: $TT = \{model, timeframe, symbol\}$ and will consider only the results obtained using one-month testing periods. Then the best results of trading the currency pairs in question can be denoted as follows: $TT1 = \{SM(SCR), H4, EURUSD\}$, $TT2 = \{MM(CCRR), H1, GBPUSD\}$, $T3 = \{SM(PP-PL, GC), H4, AUDUSD\}$, $TT4 = \{SM(PP-PL, GC), H1, USDJPY\}$. They were obtained using the commonly used in the models' testing leverage 1:100 and collected in Table 14.

Before analyzing the results, it is necessary to make a few important observations. We see that all tables show profits in absolute terms (in US dollars) and there are no relative estimates. There are serious reasons for this. Let us look at how the rate of return (return on investment, ROI) is calculated in the Forex market based on the generally accepted definition "ROI is the ratio of money received or lost to the initial investment". In the vast majority of cases, the initial deposit is considered an initial investment, forgetting about the keyword deposit.

Table 14
The best results of trading.

Period	$TT1$	$TT2$	$TT3$	$TT4$
2021.09	1194	4149	281	314
2021.10	384	1406	−852	1010
2021.11	2352	1180	−1594	−320
2021.12	800	−2180	2155	−837
2022.01	1619	−2237	2884	413
2022.02	−2436	282	587	−1575
2022.03	1555	−4290	−347	832
2022.04	168	−107	−2186	−525
2022.05	4677	−4284	2581	−111
2022.06	−1932	8542	2213	6644
2022.07	1465	1659	−1410	1004
2022.08	1901	433	3068	1000
2022.09	−4805	3885	−1084	−803
2022.10	512	2649	−1157	1665
2022.11	−1610	4761	1252	4476
2022.12	−3088	1727	−131	1520
2023.01	−1062	−1983	−1513	−2796
2023.02	−613	−1284	499	1406
2023.03	484	−2815	−120	2139
2023.04	1100	1985	567	1604
2023.05	950	−1754	1030	980
2023.06	−2999	1956	−2083	1072
2023.07	1320	1233	450	690
Sum	1936	14913	5090	19802
Month average	81	648	221	861
Winning trades	65%	65%	52%	84%

Since a trader can use any amount of this deposit greater than the minimum set by the broker, the value of the ROI completely depends on the wealth and mood of the trader. Let us assume that we traded some currency pair using 1 lot with leverage of 1:100 and an initial deposit of \$5000 and received an annual profit of \$10,000. Then we have ROI = 200%. This value of ROI may seem too large to be correct, however, it is easy to fix it. Obviously using the initial deposit of \$10,000, we will get the same profit of \$10,000 and a completely acceptable value ROI = 100%. On the other hand, the result is rather fantastic -the profit does not depend on the size of the investment. All this is a consequence of the fact that only 1 lot is actually used in trading, which with leverage 1:100 is equivalent to 1000 real dollars. The remaining part of the initial deposit is kept in the account and is not invested anywhere because of the main deposit property.

To be sure, let us look at another example. Suppose that after receiving an annual profit of \$10,000 we simply continued trading on the same terms, that is, with the same initial deposit of $10,000 and within a year we received the same $10,000 profits, so within 2 years we earned in the amount of $20,000 with an initial deposit of $10,000, while the ROI doubled, i.e., we get an absurd result. Since we came to the conclusion that the initial deposit cannot be considered as an investment, the only source of profit remains the position size (1 lot, in our case it is equal to $1,000 for the leverage 1:100), which actively participates in trading. It is important that it cannot be considered as an investment.

Let us consider an example. Suppose that 1 lot, i.e., 1000 real dollars, in our case of leverage 1:100, is an investment. By the mechanism of action such an investment is carried out with each transaction (trade). Suppose we made 300 trades in a year, which gives a total annual investment of $300,000. And this is with our deposit of $10,000. Of course, this is an absurd result. Thus considering a position size as an ordinary investment leads to absurd results. Nothing surprising, since Forex trading is based on a very specific profit-making mechanism that differs from conventional investment. Nevertheless, the properties of position size allow it to be used (unlike the initial deposit) to obtain relative estimates of trading efficiency. However, to avoid misunderstandings we will call the position size a source of profit (SOP), not an investment. Then the trading efficiency (TE) can be calculated as TE = Profit/SOP. We are well aware that despite the evidence of the conclusions made, there must be a large group of traders who are simply used to calculating ROI based on the initial deposit. Therefore, in the spirit of pluralism, we would have to supplement our tables with columns with ROI values obtained for example for the initial commonly used in the scientific papers deposit of $10,000 and as well as a column with TE values. The tables would become too cumbersome and unreadable. However, in our case, this can be avoided. Consider the annual profit $19,802 provided by the TT4 (see Table 14). Then for our case of the initial deposit of $10,000 and 1 lot trading ($1000 for the leverage 1:100) without calculations, we obtain ROI = 198.02% (division by 10,000) and TE = 1980.2% (division by 1000). Thus, in such circumstances, the additional columns for ROI and TE seem redundant. However, the problem of the multiplicity of relative estimates of trading efficiency remains open.

Therefore, in the context of our research, we propose here a compromise approach to evaluating the effectiveness of trading based on the average monthly profit and winning trades. Winning trades are calculated approximately as the number of profitable months compared to the total number of months and can be considered as an indicator of the reliability of trading, while the value of 1- Winning trades can be considered as a measure of risk. Since this approach is two criteria one, methods of aggregation of local criteria should be used, since competition between them is usually obvious.

However, in our case, this is not necessary (see Table 14). Indeed, TT4 provides the greatest averaged monthly profit and reliability, and therefore is the best one. The remaining TTs have equal reliability and can be ranked according to their average monthly profit. Then we get the following rating: TT4 – > TT2 – > TT3 – > TT1. So, if we want to make a starting decision (buy or sell) on 01.09.2022, we have to do it based on TT4 as an adviser and continue trading until TT4 fails. Then we have to switch to the TT, which works better at the moment.

In the literature, we can find many works describing various methods and approaches to building automated trading systems (ATS) developed to work on financial markets such as Forex, NYSE, NASDAQ, etc. However, our experience suggests that not all significant details are typically presented in published works, which in practice makes it impossible to reproduce them correctly and then effectively implement them. Results returned by a reproduced selected trading system, developed based on incomplete information, could be considered unreliable and unsuitable for use as reference values for the results obtained within the approach proposed in the current paper. In addition, according to the experience of traders, the available quotes depend significantly on the broker providing the data, the time zone in which we are located, the version of the MetaTrader 4 platform used, etc. This further complicates the problem. Therefore, hereinafter, in this article, only the results obtained using the simple BSH strategy (Buy or Sell and Hold) will be used as comparative values. This is not a new invention, as the BSH-based approach was used as a basic one in many papers (Carta et al., 2021; Fisichella & Garolla, 2021; Hernandez-Aguila et al., 2021; Kaczmarek et al., 2022; Munkhdalai et al., 2019; Nobre & Neves, 2019; Ozer & Sakar, 2022; Ramezanian et al., 2019; Sadeghi et al., 2021), etc.

The BSH strategy assumes the retention of an active market position throughout the entire investment period. In practice, this means opening a market position at the beginning of the investment period (01.09.2021) and closing it only at the end of the above period (31.07.2023). It was assumed in this study that for selected financial instruments (currency pairs), positions providing profits were opened. Thus, for TT1, TT2, and TT3, these were Short positions, while for TT4, it was a Long position. In addition, it was assumed that the initial market value of each position would be equal to the initial account balance (balance) used in the research, which was $10,000. The profits obtained using the BSH strategy are as follows: $12,506, $16,429, $7293 and $22,488 from TT1, TT2, TT3 and TT4, respectively.

It can be seen that these results are somewhat superior (not so strong) to the results obtained using our model (see Table 14). However, this is a typical situation when we are dealing with strong and relatively smooth trends, as, for example, in our case. Later, we will return to the analysis of the BSH results in the context of a multimodel strategy. It was argued that for reliable testing of a strategy, it was necessary to use data for the last 3–5 years. And this was justified because the timeframes 1 week and 1 day were used and the market behavior was much more predictable than it is now. But since we use intraday trading, we have made more trades in a year than when using a 1-day timeframe in 3 years. Therefore, in the literature, we can find many articles (Dymova, Kaczmarek, & Sevastianov, 2021; Moghaddam & Momtazi, 2021; Ozturk et al., 2016; Santis et al., 2021; Sarangi et al., 2022; Uddin, 2021; Yuan & Chao, 2021; Zafeiriou & Kalles, 2023), where trading systems were tested on data covering periods lasting from several months.

The results obtained (Table 14) are based on 23 months of trading. Is this enough to get reliable results? In the good old textbooks written in the quiet pre-computer era, it was argued that for reliable testing of the strategy, it was necessary to use data for the last 3–5 years. And this was justified because the timeframes 1 week and 1 day were used and the market behavior was much more predictable than it is now. But since we use intraday trading, we have made more trades in a year than when using a 1-day timeframe in 3 years. There is a widespread opinion that in order to get a reliable average of something, it is necessary to use as large a sample as possible. This is correct, but only if the sample is homogeneous. Otherwise, the average value is just meaningless (see any statistics textbook). Suppose that in our case it was decided to increase the reliability of the estimate of the average monthly profit by including data from 2021 in the analysis. Would such a two-year sample be more reliable? Obviously not — in 2021 there was no global energy crisis, the problems of the dollar as a reserve currency was not visible and there was no war in the center of Europe: it was another world and another Forex. Thus, the sample consisting of the profits received over the past two years cannot be homogeneous, and the corresponding averaging becomes senseless. Taking into account the above, let us assume that during 2021, a negative average monthly profit was obtained for TT1, and the results for 2022 did not change. This negative profit over the past 2021 cannot affect our decision to choose TT1 for trading in early September 2022. Moreover, as can be seen from Table 14, it is more than enough to analyze the results over the past 4–6 months to make the right decision, especially since we always trust the latest results obtained in market conditions close to

Table 15
Cumulated profits in different time periods.

	TT1	TT2	TT3	TT4
2021.09–2022.08	11747	4553	7380	7849
2022.09–2023.07	−9811	10360	−2290	11953
2021.09–2023.07	1936	14913	5090	19802

those in which we will trade. In this context, Table 14 contains more than enough (excessive) information to make the right decisions.

Currently, in algorithmic trading, the optimal duration of the optimization period is estimated not in days months, or years but in the number of completed transactions. Let us explain this by example, Let us say we test the strategy for 10 years (at first glance, more than enough) and make one transaction every month, so we have 120 transactions in total and this is a very bad result. According to researches and the common experience of MQL5 community (an international internet organization uniting algorithmic traders) optimization on such a small number of trades will almost always lead to losses during test periods mainly due to the overfitting effect. Obviously, it is impossible to establish a certain universal allowable minimum number of trades in optimization periods, Nevertheless, within the MQL5 community, there is a general opinion based on experience that this number varies in the range of 250–350 and, very importantly, regardless of the calendar time and the timeframe used. Since our simple models generated 310–600 transactions per year, we can say that such an optimization period (one year) is quite sufficient for our research.

Then let us turn to our case. We got our results using 23 months of testing with about 1000 transactions. Thus, we used 1.7 times more transactions than was required to obtain reliable results. In addition, if we consider 1000 transactions in the case of day-to-day trading, we will find that this is equivalent to more than 4 calendar years of trading. We think this is a convincing result.

Let us turn to the analysis of the Table 14. It is easy to see that the data in this table can be represented by two periods 2021.09–2022.08 and 2022.09–2023.07 (see Table 15).

If we look at the weekly and monthly charts of the four currency pairs under consideration, we will see that the end of the first period is characterized by a strong and relatively smooth upward trend of the US dollar, and in September there is a sharp trend reversal, followed by a strong downward trend of the US dollar in the second period. This power reversal of trend was caused by a very important international-scale macro economical event: on September 8, 2022, the European Central Bank made, according to Reuters, an unprecedented decision, raising the base interest rate on loans by 75 basis points in order to combat inflation. We can see that TT1 and TT3 based on the H4 timeframe give better results than TT2 and TT4 based on the H1 timeframe in the first period and fail in the second. It is not surprising that such global changes in the trend of the main currency can only be caused by significant changes in global markets and not every even very complex model can survive such events. Meanwhile, TT2 and TT4, being more complex (detailed) and based on the H1 timeframe, provide a relatively low but positive profit in the first period and a considerably larger profit in the second period. Therefore, their profit accumulated over all the analyzed 23 months seems very attractive. Thus, if we prefer to use a single model approach, then based on the data from Table 14 or Table 15, we should choose TT4. However, a more attractive option is to combine the best results of the first period and the best results of the second, i.e. at the beginning we trade TT1 and switch to TT4 at the beginning of the second period. In this case, we get a total profit $23,700 that significantly exceeds the profit $19,802 from using TT4 alone. Strictly speaking, this is the key idea of our multi-model approach, presented in an approximate but transparent form. Of course, we can say that it is easy to get good results based on a posteriori analysis, while in practice we do not know the future. Therefore, there is a problem of practical implementation of this idea. Here we will present this implementation as sequential steps with illustrations.

There are various ways to use the data presented in to improve overall trading results. The most obvious is the development of an optimal portfolio based on $TT1 - TT4$. This is an interesting and potentially profitable area of our future research, but in this article we will consider a simpler approach (we call it an approach based on leader correcting (ALC)) reflecting the specifics of the data, such as in Table 14. For the sake of simplicity, here we consider only the first time period (see Table 15). Then we can see that $TT1$ (the leader) is much superior to $TT2 - TT4$. Therefore, it is quite natural to trade mainly $TT1$, switching to $TT2 - TT4$ only in those months when $TT1$ loses money.

Let us simulate this approach in detail based on the data in Table 14. It is seen (Fig. 30) that we successfully traded $TT1$ until 2022.02.01, as can be seen in Table 14. However, at the beginning of this month we note systematic losses. Let us assume that we are able to tolerate this until the losses exceed a certain threshold, the value of which strongly depends on the subjective preferences of the trader, or until the losses last no longer than a certain time. According to our observations, there are 8 Bars that are quite suitable for this critical time, which correlates with the average values of the number of consecutive losses obtained in our studies. In Fig. 30, we see that such stable and significant losses are observed on the first eight Bars that we can judge the high probability of such a downtrend continuing in the future (of course, according to the conditions of our simulation, we cannot accurately predict the future).

Therefore, it is worth evaluating the feasibility of switching at this moment to trade in other trading tools ($TT2 - TT4$). As a result, we came to the conclusion that it is inappropriate to switch trading to $TT2$ and especially to $TT4$ in contrast to $TT3$ (see Fig. 31). In this figure, we see a strong profit growth on Bars 4–8 and therefore switch from $T1$ to $T3$. As a result of the operations carried out, a very small, but positive monthly profit was obtained, which is much better than the large losses that would have been received this month in the continuation trading on $TT1$.

In Figs. 30 and 31, we see the relatively antiphase behavior of $TT3$ and $TT4$ after the eighth Bar. Therefore, if we were trading simultaneously on $TT1$ and $TT4$ this month, positive and negative results would be annihilated, at least reducing total losses or even providing a small total profit. This is an argument in favor of using portfolio approaches if there is no pronounced leader among the available TTs.

Let us consider the next more convincing example (Figs. 32–35). Suppose from the end of the second month, we continued to trade successfully on $TT1$ until at the beginning of the sixth month we found systematic losses on the first eight Bars (Fig. 32). So we see the prerequisites for a temporary switch of trading to other TT. In Fig. 33, we see that at the eighth Bar, the $TT2$ rather provides a moderate downtrend of profit (we cannot see the future), and therefore we exclude $TT2$ from further analysis.

In the cases of $TT3$ and $TT4$ up to the eighth bar, we see a stable uptrend of profit. Since at the same time $TT4$ provides significantly more profit on the eighth bar than $TT3$, it is advisable to switch from $TT1$ to $TT4$. The final profit of this trade, calculated as $TT4$ profit from the 8th bar to the end of the sixth month — $TT1$ loss from the beginning of the sixth month to the 8th bar, is about $4,000, while the final profit in the case of switching to the $TT3$ is about $2,000.

The last example performs the ability of the proposed "approach based on leader correcting" to compensate for the evidenced negative overfitting effect (Fig. 32) by the positive overfitting one (Figs. 34 and 35) with great resulting profits. The described approach is not completely formalized and needs some interventions of a trader and manual work. Therefore, here we present a formalized but a bit less profitable algorithm than that described above.

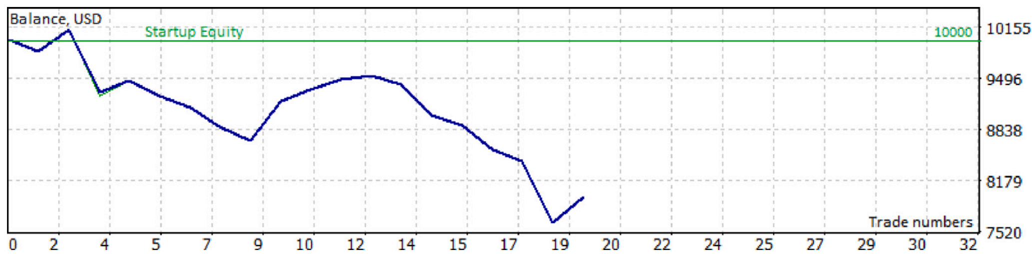

Fig. 30. $TT1$, 2022.02 testing period.

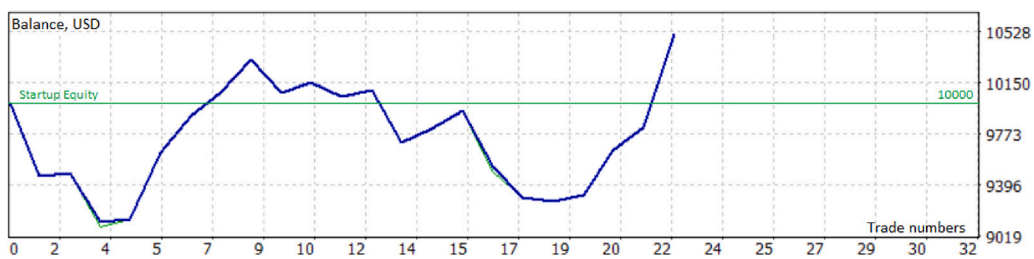

Fig. 31. $TT3$, 2022.02 testing period.

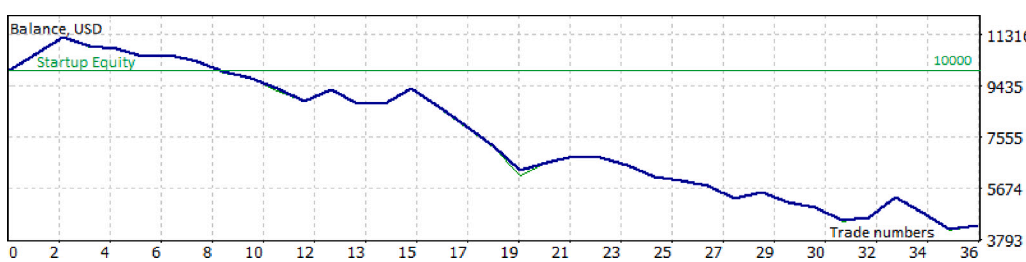

Fig. 32. $TT1$, 2022.06 testing period.

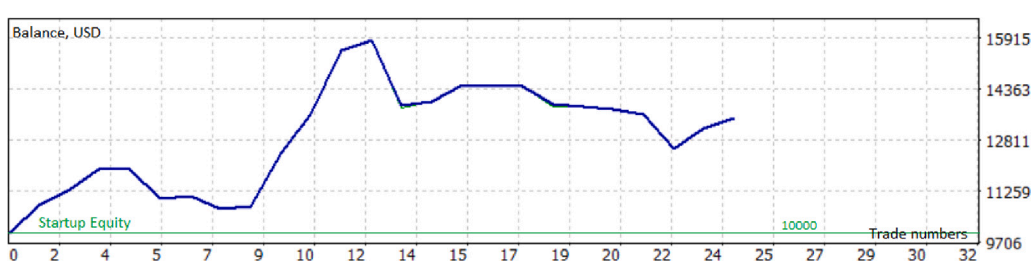

Fig. 33. $TT2$, 2022.06 testing period.

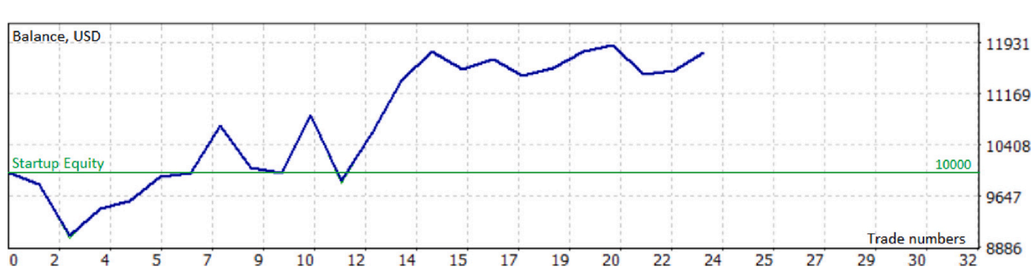

Fig. 34. $TT3$, 2022.06 testing period.

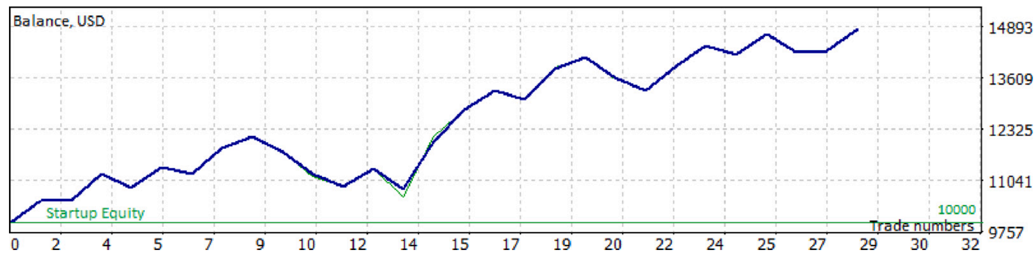

Fig. 35. $TT4$, 2022.06 testing period.

One of the most important decisions of an investor operating in the Forex market is the decision related to choosing a financial instrument (trading tool, TT). This type of choice is never obvious and is usually strongly determined by the current market conditions at the moment. Therefore it is worth considering an approach based on the parallel monitoring of a specific number of selected TTs in order to change the current TT in case it starts to generate unsatisfactory results. Of course, it would be best if the results returned by the TTs under consideration were not strongly correlated with each other as is the case of TT1-TT4, presented in Table 14. The sequent steps of the proposed approach are presented in Algorithm 1. In the beginning, n TTs should be selected, appropriate adaptation should be provided (e.g. optimization process), and then the selection of the best TT for the next investment period should be done. In the proposed solution, it is a TT that returned the highest accepted profit in the period immediately preceding the current period (see line 5). At the beginning of an investment period, a position is opened and it will be closed at the end of this period (see lines 10). At the beginning of the next investment period, the assessment of the result obtained in the previous period is carried out and if it is negative, then there is a switch to the TT that in the completed period provided the highest result (see lines 12–13). In the case, when in the last investment period, none of the n TTs under consideration have provided an acceptable investor result (see Line 14) then we can start the whole procedure from the beginning (perhaps with a corrected set of TTs) (see Line 3) or refrain from investing in this period to re-evaluate the TTs (see Lines 14–15). In Table 16, the results of simulations obtained with the use of the developed approach (Algorithm 1) are presented. Table 16 presents 4 scenarios based on different TTs used as starting TT in the process of simulation. Upper indices for particular monthly profits indicate which TT was used during the period. It was assumed that while simulating, the switch of TT will be made only if in the previous period there was a loss (profit<0). In these circumstances, there was a switch to the TT providing the greatest positive profit in the last period. Performing Table 16 analysis, it can be noted that starting from the period 2022.03 all scenarios in subsequent periods use the same TTs tools. This is due to the specification of our approach (Algorithm 1) and the fact that under real conditions it is almost impossible to have TT that will always generate profits.

Successive TTs switching (after losses occurred) has caused that since that period all scenarios have become convergent. The above situation is not a disadvantage and can already be identified with the fact of striving to find the best solution. In Table 16, special attention should be paid to the period 2023.01, in which all TTs provided negative profits (losses). In these types of cases, we have two options: start the whole procedure over again or refrain from investing within the immediate period. In Table 16, the latter option is applied, hence the lack of results for the period 2023.02.

In Table 16, we can see that the average monthly profits obtained using the multi-model approach in all fourth possible scenarios are significantly greater (in one case more than 14 times greater) than those we get using a single-model strategy. The relative numbers of winning trades, characterizing the strategy reliability, are significantly greater for the multi-model approach as well. In the case of the single-model approach, we obtained 7–9 losing months, whereas the multi-model approach brought us only 4–5 losing months. Thus the multi-model approach is significantly most riskless. Finally, in Table 17, we can see that although the considered simple models generated slightly smaller profits than the BSH strategy, their use in the framework of a multi-model approach sometimes brings profits 2–3 times greater than the BSH.

Algorithm 1 An algorithm the multi-model trading

1: t ▷ current investment period (e.g. the whole month of May)
2: **repeat**
3: selection of Trading Tools ← TT1, TT2, ..., TTn
4: optimization process(TT1(t-1, ...,t-m), TT2(t-1, ..., t-m), ..., TTn(t-1, ..., t-m)) ▷ $t-1,...,t-m$ → archival data
5: $TT \leftarrow max\{Profit(TT1(t-1)), Profit(TT2(t-1)), ..., Profit(TTn(t-1))\}$ ▷ determining the best trading tool
6: **until** $Profit(TT(t-1)) < expected\ profit$
7: opening a market position (TT)
8: **while** $System\ stop \neq True$ **do**
9: **if** $end\ investment\ period = True$ **then**
10: closing the market position ▷ $Profit(t)$
11: **else if** $new\ investment\ period = True$ **then** ▷ $t \leftarrow t+1$
12: **if** $Profit(TT(t-1)) < expected\ profit$ **then**
13: $TT \leftarrow max\{Profit(TT1(t-1)), Profit(TT2(t-1)), ..., Profit(TTn(t-1))\}$ ▷ new trading tool
14: **if** $Profit(TT(t-1)) < expected\ profit$ **then**
15: making a decision: reoptimization or waiting for the next investment period
16: **end if**
17: **end if**
18: opening a market position (TT)
19: **end if**
20: **end while**

Our research allowed us to formulate very soft requirements for the models used in the multi-model approach Such models (not necessarily simple) optimized independently should be sufficiently profitable at least for some periods and be no more than weakly correlated.

The above results should not be considered as a practical advice, since, according to our experience, they vary greatly depending on the broker providing the data, the time zone in which we are located, the version of the MetaTrader 4 platform used, etc. The main purpose of this article is not to present the good results obtained, but to substantiate the newly developed approaches for obtaining such results.

6. Conclusion

In this paper, based on the declared methodological foundations, a set of simple, but profitable trading models is developed. To do this, new technical analysis indicators and trading rules were introduced.

Table 16
Simulation of the multi-model trading (MMT).

Period	Profits	MMT results			
	{TT1, TT2, TT3, TT4}	start: TT1	start: TT2	start: TT3	start: TT4
2021.09	{1194, **4149**, 281, 314}	$1194^{(TT1)}$	$4149^{(TT2)}$	$281^{(TT3)}$	$314^{(TT4)}$
2021.10	{384, **1406**, −852, 1010}	$384^{(TT1)}$	$1406^{(TT2)}$	$-852^{(TT3)}$	$1010^{(TT4)}$
2021.11	{**2352**, 1180, −1594, -320}	$2352^{(TT1)}$	$1180^{(TT2)}$	$1180^{(TT2)}$	$-320^{(TT4)}$
2021.12	{800, −2180, **2155**, -837}	$800^{(TT1)}$	$-2180^{(TT2)}$	$-2180^{(TT2)}$	$800^{(TT1)}$
2022.01	{1619, −2237, **2884**, 413}	$1619^{(TT1)}$	$2884^{(TT3)}$	$2884^{(TT3)}$	$1619^{(TT1)}$
2022.02	{-2436, 282, **587**, -1575}	$-2436^{(TT1)}$	$587^{(TT3)}$	$587^{(TT3)}$	$-2436^{(TT1)}$
2022.03	{**1555**, −4290, −347, 832}	$-347^{(TT3)}$	$-347^{(TT3)}$	$-347^{(TT3)}$	$-347^{(TT3)}$
2022.04	{**168**, −107, −2186, -525}	$168^{(TT1)}$	$168^{(TT1)}$	$168^{(TT1)}$	$168^{(TT1)}$
2022.05	{**4677**, −4284, 2581, -111}	$4677^{(TT1)}$	$4677^{(TT1)}$	$4677^{(TT1)}$	$4677^{(TT1)}$
2022.06	{-1932, **8542**, 2213, 6644}	$-1932^{(TT1)}$	$-1932^{(TT1)}$	$-1932^{(TT1)}$	$-1932^{(TT1)}$
2022.07	{1465, **1659**, −1410, 1004}	$1659^{(TT2)}$	$1659^{(TT2)}$	$1659^{(TT2)}$	$1659^{(TT2)}$
2022.08	{1901, 433, **3068**, 1000}	$433^{(TT2)}$	$433^{(TT2)}$	$433^{(TT2)}$	$433^{(TT2)}$
2022.09	{-4805, **3885**, −1084, -803}	$3885^{(TT2)}$	$3885^{(TT2)}$	$3885^{(TT2)}$	$3885^{(TT2)}$
2022.10	{512, **2649**, −1157, 1665}	$2649^{(TT2)}$	$2649^{(TT2)}$	$2649^{(TT2)}$	$2649^{(TT2)}$
2022.11	{-1610, **4761**, 1252, 4476}	$4761^{(TT2)}$	$4761^{(TT2)}$	$4761^{(TT2)}$	$4761^{(TT2)}$
2022.12	{-3088, **1727**, −131, 1520}	$1727^{(TT2)}$	$1727^{(TT2)}$	$1727^{(TT2)}$	$1727^{(TT2)}$
2023.01	{-1062, −1983, −1513, -2796}	$-1983^{(TT2)}$	$-1983^{(TT2)}$	$-1983^{(TT2)}$	$-1983^{(TT2)}$
2023.02	{-613, −1284, 499, **1406**}				
2023.03	{484, −2815, −120, **2139**}	$2139^{(TT4)}$	$2139^{(TT4)}$	$2139^{(TT4)}$	$2139^{(TT4)}$
2023.04	{1100, 1985, 567, **1604**}	$1604^{(TT4)}$	$1604^{(TT4)}$	$1604^{(TT4)}$	$1604^{(TT4)}$
2023.05	{950, −1754, 1030, **980**}	$980^{(TT4)}$	$980^{(TT4)}$	$980^{(TT4)}$	$980^{(TT4)}$
2023.06	{-2999, 1956, −2083, **1072**}	$1072^{(TT4)}$	$1072^{(TT4)}$	$1072^{(TT4)}$	$1072^{(TT4)}$
2023.07	{1320, 1233, 450, **690**}	$690^{(TT4)}$	$690^{(TT4)}$	$690^{(TT4)}$	$690^{(TT4)}$
Month Average	{81, 648, 221, 861}	1135	1313	1047	1007
Winning trades	{65%, 65%, 52%, 84%}	83%	83%	78%	78%
Sum	{1936, 14913, 5090, 19802}	26095	30208	24082	23169

Table 17
The resulting comparison.

	Single model approach	BSH approach	Multi-model approach
TT1	1936	12506	Start from TT1: 26095
TT2	14913	16429	Start from TT2: 30208
TT3	5090	7293	Start from TT3: 24082
TT4	19802	22844	Start from TT4: 23169

The methods to design profitable simple models and the corresponding problems were presented. Moreover, the overfitting problem was analyzed and the concepts of the positive and negative overfitting were introduced and used in the analysis. The study of the selected simple models' profitability and reliability, based on the currency pairs EURUSD, GBPUSD, AUDUSD and USDJPY, selected as sufficiently volatile relative to the real spreads provided by the broker, was carried out. To implement a general approach to the trading process modeling, a multi-model simulation called "the approach based on the correction of the leader", was developed. It was proved that this approach is able to offset the evidenced negative overfitting effect by the positive overfitting one with great final profits. The appendices contain several complete codes of our trading support applications, ready for use on the popular MetaTrader 4 platform.

The scientific significance of the article lies in the fact that for the first time on the real-world example of the Forex market it was shown that complex detailed mathematical models of real processes can be replaced by a set of simplified models with significant methodological and practical advantages. The formulated principles of constructing a set of simplified mathematical models are quite general and can be applied in various fields, and not only for trading on the Forex market. The practical importance of this work is that the developed models, which fully ready-to-use codes are provided in Appendices, can be used directly or after some adaptation for trading, not only securities but CFD contracts and Futures, as well, while gaining implicit access to wide markets of stocks and commodities. An important limitation of these models is that they cannot be used directly for classical stock trading when so-called short sales are forbidden.

Forex is a decentralized market. Therefore any broker provides its own rates which makes impossible the correct comparison of the trading models provided by different developers. This is the fundamental Forex limitation concerned with not only our models.

This article presents the results of the first stage of our research. The next step will be the development of multiple-criteria fuzzy trading models developed as extensions of the models presented in the current article.

The current paper only casually touches on such an important aspect as risk analysis. At the same time, in all our models there are parameters StopLoss and TakeProfit representing two different types of risks directly in USD. Their optimal values are obtained taking into account their dependence on the degree of market variability, and along with the values of other parameters as a part of profit maximization task solution. Unfortunately, these parameters, which are the input variables of the model, are difficult to use for analyzing trading risks. Suppose we have calculated some averaged StopLoss value, then we cannot say that this value provides high or low risks, since it can be only the optimal value that makes sense only for a certain model under certain conditions. Therefore, it seems more promising to use the output parameters of the model.

The simplest one is the ratio of the number of unprofitable transactions to the total number of transactions, reflecting the risk of unprofitable transactions. The total trade parameter (TT) reflects the risk of negative overfitting, which increases along with a decrease in IT. The relative drawdown parameter (RD) represents the risk of an increase in drawdown with an increase in RD, etc. Of course, this list can be extended, here we describe only the most obvious sources of risk.

Based on our previous analysis, we can distinguish three groups of local trading quality criteria: profit-dependent criteria, for example, based on $Gross\ profit$ and $Gross\ loss$, which have different importance; risk-dependent criteria described above, criteria of trading comfort, for example, based on the $\%\ of\ Winning\ trades$ and $Relative\ profit(RP)$, $RP = (GrossProfit - GrossLoss)/GrossProfit$. All these local criteria have different importance, and their weights are obtained together

Table A.18
List of terms.

Term	Description
Bar	Graphical representation of the price volatility (OHLC — Open, High, Low, Close) of a given financial instrument in a given period, e.g. 1H (1 h).
Timeframe	Time frame (e.g. 1H - 1 h, 4H - 4 h) within which data coming from the market are aggregated.
Bid	The price at which the market is prepared to buy a product.
Ask	The price at which the market is prepared to sell a product.
Spread	The difference between the bid and the ask price.
Long position	A position that appreciates in value if market price increases.
BUY	Taking a long position on a product.
Short position	An investment position that benefits from a decline in market price.
SELL	Taking a short position in expectation that the market is going to go down.
Lot	A unit to measure the amount of the deal e.g. EURUSD 1 lot = 100k. (e.g. value of the first transaction rate in a given period - Open, value of the last transaction rate - Close, etc.).
Volume (one position)	The size of a given market position expressed in a lot.
Volume (one timeframe)	The total volume of all transactions executed during the period (timeframe).
Profit	It defines the value of profit/loss obtained from a given market position. In practice, it is the result of the product of the position size (volumen) and the difference between the cost price and the selling price, minus the transaction costs.
Gross Profit	Total profit from all closed profitable positions.
Gross Loss	Total loss from all closed losing positions.
Total trades (% of total)	Total number of closed market positions/trades (percentage of winning positions).
Profit trades	Number of all profitable trades.
Loss trades	Number of all losing trades.
Total net profit	The total profit/loss obtained from all closed trades.
Balance	The current balance of the account (investment account) after taking into account all closed positions, given in the base currency.
Startup Equity	The value of the initial balance of the investment account in the base currency (deposit).
Equity	The current value of the current account balance (balance) plus the profit/minus the loss of the currently open positions.
Balance curve	The curve presenting the current account values (balance), resulting from the closing of successive market positions (balance(position number)).
Stop Loss	It defines the maximum level of acceptable losses, in practice it is the value of the exchange rate at which the order to automatically close a loss-making position will be activated.
Take Profit	It defines the target level of profit, in practice it is the value of the rate at which the order to automatically close the position bringing profit at the expected level will be activated.
Profit Factor	The ratio between gross profits and gross losses. Profit Factor below 1.0 means that the trading system is loss-making.
Relative drawdown	The percentage between the difference of the maximum equity high and the subsequent equity low to the maximum equity high.

with other undefined parameters as a solution to the multiple-criteria optimization problem.

It is easy to see that a set of local criteria can be represented by a hierarchical structure. To make trading models flexible, in future research, we will present local criteria in the form of corresponding membership functions of fuzzy subsets.

CRediT authorship contribution statement

Pavel Sevastjanov: Conceptualization, Formal analysis, Investigation, Methodology, Resources, Supervision, Writing – original draft, Writing – review & editing. **Krzysztof Kaczmarek:** Formal analysis, Investigation, Methodology, Resources, Software, Writing – original draft, Writing – review & editing. **Leszek Rutkowski:** Formal analysis, Methodology, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

See Table A.18.

Appendix B

SimplestModel($dSMA$) presented in this study are available at Listing1
(https://cloud.icis.pcz.pl/s/obazjWFPZKj9w8E).

Appendix C

SimplestModel($PP - PL$) presented in this study are available at https://cloud.icis.pcz.pl/s/SmxZWf9orwditQe Listing 2
(https://cloud.icis.pcz.pl/s/SmxZWf9orwditQe).

Appendix D

Simple model($PP - PL$) presented in this study are available at Listing3
(https://cloud.icis.pcz.pl/s/CtWf9BgJNk3ry9y).

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