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Research Article

Hybrid Cyber-Physical Stock Exchange Robot with Artificial Intelligence and Fuzzy Module

Nikolay Lomakin [1,*], Skhvediani Angi [2], Alexey Kizim [1], Ivan Lomakin [1], Tatyana Boriskina [1], Ekaterina Kosobokova [3], Alena Kuzmina [1], Elena Samsonova [1]

[1]*Volgograd State Technical University, 400005, ave. V.I. Lenina, 28, Volgograd, Russia*
[2]*Peter the Great St. Petersburg Polytechnic University, 195251, Polytechnicheskaya, 29, St. Petersburg, Russia*
[3]*Volgograd branch of REU named G.V. Plekhanov, 400005, at. Volgodonskaya, 13, Volgograd, Russia*
**Corresponding author: mmiop@vstu.ru; Tel.: +7-903-3176642*

Abstract: In modern conditions, the use of trading algorithms based on artificial intelligence, as well as mathematical algorithms, including fuzzy ones, which operate as a single system, which ensures the efficiency of trading operations, is very relevant. Despite a significant number of scientific papers on this topic, individual aspects have not been sufficiently studied, and there are some gaps that require additional research. The relevance lies in the fact that the algorithms of hybrid CP systems are increasingly used in exchange trading, increasing its efficiency. The scientific novelty lies in the fact that the authors proposed the simultaneous use of two algorithms in the trading bot: the deep learning model "Random Forest" (DL) and the fuzzy learning algorithm, which operate as a single system (GCFS). During the study, an exchange trading bot, a hybrid cyber-physical system, was formed. This study aims to develop a hybrid cyber-physical system (HCS) containing a DL model and a fuzzy algorithm. Methods used in the study: hybrid cyber-physical system, deep learning model, and fuzzy algorithm. The significant conclusion is that the goal has been achieved and the cyber-physical system has been successfully developed. One of the factors of the bot's effective trading is the low error in asset price forecasting. For example, the average absolute error of the MCE does not exceed USD 0.9495 or 0.11%. Fuzzy provides profit, in our example $2.10 positive margin of $2.10, instead of a negative margin of $1.61, for 11 minutes of trading one contract.

Keywords: Deep learning; Exchange robot; Fuzzy; Hybrid cyber-physical system; Price forecast; SiU4 futures

1. Introduction

During the study, a stock exchange trading bot, a hybrid cyber-physical system (HCPS), was formed. In modern conditions, using trading algorithms based on AI, as well as mathematical algorithms, including Fuzzy, which work as a single system, is very important to ensure the efficiency of trading operations. A significant conclusion is that a hybrid cyber-physical system (HCPS), a deep learning (DL) model, and a fuzzy algorithm were successfully developed, which increased the trading system's efficiency.

The scientific novelty lies in the fact that the authors proposed using two algorithms simultaneously in the trading bot: the deep learning model "Random Forest" (DL) and the fuzzy algorithm, which work as a single system (GCFS), which eliminates deposit drawdowns during the

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working timeframe and thereby increases the efficiency (profitability) of speculative operations by the bot.

Despite a significant number of scientific works on this topic, individual aspects have not been sufficiently studied. There are some gaps, in particular, in the issues of interaction of various modules of the trading system, as well as identifying factors that determine the dynamics of parameters important for the effectiveness of its work, which requires further research.

The profitable operation of exchange trading robots and the factors that determine their effectiveness have become the subject of research by several scientists and exchange traders. Many scientific studies have been conducted by various scientists to identify the factors that influence the profitability of algorithmic trading systems during their application and to identify the existing relationships between the factors that influence the accuracy of the forecast of the stock market price during trading. This study continues the long list of studies on this topic. However, the main focus is on the study of a certain cyber-physical system and models used both in forecasting the price of a financial instrument CiU4 using deep learning and in making a buy/sell decision on this asset using the fuzzy algorithm.

The study aims to improve forecasting accuracy, thereby ensuring the effectiveness of stock exchange trading operations using trading robots based on artificial intelligence.

Many modern scientists devote their work to the use of CPS in stock trading robots. For example, Lomakin N.I. and colleagues are developing a similar cyber-physical system for use in a stock trading robot, which not only uses the deep learning algorithm "random forest", but also an algorithm for monitoring the stock order book in real time, which allows to increase the trading efficiency (Lomakin et al., 2024). A team of authors led by Dhyani A. based on the study examines financial technologies have had a strong impact on the stock market, contributing to the profitability and efficient operation of the stock exchange (Dhyani et al., 2023). A group of authors, including Akhil Raj Azhikodan, have done a proof of concept work demonstrating that RL can be used for stock trading. The system created in the study works on a single company stock; however, its convolutional neural network architecture can be scaled up to use stocks of multiple companies. Coordination between multiple networks will be required in the process of scaling this project. The main NN will look at the actions predicted by the networks and choose the best action among them (Azhikodan et al., 2019). The trading method used by the authors was modeled as a MDP. The environmental states were designated as follows. $s_t \in Sa_t \in Ar_i \in Rt \ \in \{0, 1, 2, 3 \ldots\}$ (see equation 1).

$$P^{a}_{ss'} = P_r\{s_{t+1} = s' | s_t = s, a_t = a\}, \quad (1)$$

Result (Equation 2):

$$R^{a}_{s} = E\{r_{t+1} | s_t = s, a_t = a\}, \quad (2)$$

The trading robot's decisions correspond to the policy π (see equation 3):

$$\pi(s, a, \theta) = P_r\{a_t = a | s_t = s, \theta\}, \quad (3)$$

where: $\theta \forall s \ \in A\pi(s, a, \theta) \ \pi(s, a)$ (see Equation 4).

$$R_t = \sum_{k=0}^{\infty} \gamma^k \, r_t + k, \quad (4)$$

where: γ - is a discount factor that takes values from 0 to 1 and is called the discount factor.

These rewards are standardized and included in the backpropagation for each episode. In this case, the RL agent, which is a neural network, is trained on several episodes for optimization. Under the supervision of Kostas et al. (2017), the authors' research studies new areas that reveal the features of working with cyber-physical systems, the Internet of Things (IoT), fifth-generation mobile systems, 5G, and end-to-end decision-making, as well as systems for designing similar systems (SoS/E). The authors illustrate concepts related to large and small systems (Kostas et al., 2017).

Qifa Xu with his colleagues combined an unlimited mixed data sample (UMIDAS) and a support vector quantile regression (SVQR) to simultaneously solve two problems related to mixed frequency data and modeling nonlinear relationships to propose a new UMIDAS-SVQR model within the quantile regression. According to the author, this is of great importance in developing the main directions of the investment development strategy, forming a forecast price of shares and successfully managing the exchange portfolio in conditions of market uncertainty (Xu et al., 2019). In his study, Pedro offered a brief historical overview of related subject areas, namely the theory of control, information and cybernetics. The author makes a necessary digression from philosophical positions and possible misinterpretations of broad theoretical constructs such as cyber-physical systems (Pedro, 2022).

Sarthak et al. proposed a stock trading strategy that used reinforcement learning algorithms to maximize profits. The proposed strategy uses three actor critic models: Advanced Actor Critic (A2C), Twin Delayed DDPG (TD3), and SAC. The developed strategy can select the most optimal model based on the current market situation. To evaluate the performance of the developed trading bot, Markowitz portfolio theory is compared (Sarthak et al., 2022). Abdel et al. (2021) presented a new model for multi-stock trading based on free synchronous multi-agent deep reinforcement learning. The developed model can interact with the trading market to capture the dynamics of the financial market. The strong advantage of the proposed model is its ability to use datasets with different characteristics from the US stock market with huge historical data (Abdel et al., 2021).

Studying the structure of the secondary market, namely the mechanism of competition's influence on algorithmic and high-frequency trading, some experts highlight the mechanism showing how exactly competition influences algorithmic trading and conclude that significant changes have occurred in the stock market's structure. Fuzzy algorithms are widely used in practice not only in enterprise economic management (Kang et al., 2023) but also in the process of forming fuzzy networks for assessing the states of models, using Markov chains when used in algorithmic trading (Dimirovski, 2005).

According to some experts, using an approach based on the use of graphical models, which makes it possible to optimize the process of forming reliable exchange portfolios, is advisable. The most popular models of this class, experts include such as PCA, KMeans, and dynamic blusterers. In addition, automatic encoders, which are capable of searching for patterns in large covariance matrices as they change over time, are recommended for use. Approaches proposed by scientists

The use of the VaR model to assess financial risk allows for risk reduction not only in the process of exchange trading but also in the financial market as a whole. Bambang Prasetya and a group of his colleagues Bambang Prasetya identified key factors influencing risk management, analyzed the standardization of innovations, and provided recommendations for improvement based on risk (Prasetya et al., 2023). Enterprise risk management was studied by Anton and Nucu (2020) who conducted a broad review of the literature on the problems of risk and financial management.

Although the process of scaling algorithmic exchange trading is developing unevenly around the world, it is becoming a leading paradigm that supports traders, investors, and programmers in identifying, assessing, and managing risks at the level of algorithmic trading systems. Scholars have studied this process, but there is no complete picture of the determinants and consequences of such an integrated process. Therefore, we present an empirical review of the literature, allowing us to draw certain conclusions regarding the development of this process.

Decision trees (DTs) are a supervised learning method with nonparametric characteristics that are traditionally used for classification or regression problems. Creating a model for generating predictive values of the target variable is the final result of applying the method. The model, learning the rules extracted by the method from the characteristics of the data, resembles a piecewise constant approximation. A feature of the algorithm is that the set of accepted rules becomes more complex with an increase in the size of the tree, but, as a rule, the forecast is more accurate. However, the most accurate forecasts can be obtained using the random forest method, which includes an ensemble or set of decision trees.

Igor Nikolaevich Lyukevich and co-authors proposed the use of three exponential moving averages and a stochastic oscillator in constructing a multi-timeframe trading strategy (Nikolaevich et al., 2020). Simultaneously, the authors tried to prove the hypothesis about the possible adaptation of high-risk currency market strategies to low-risk market shares, which are based on a multi-timeframe analysis of the intersection of 3 EMA and the use of a stochastic oscillator.

Testing of trading strategies based on moving averages was carried out by Huang and Huang (2020). The authors found that, compared with the buy and hold strategy, MA strategies have a lower average return and Sharpe ratio but show better results, with higher efficiency indicators. The authors concluded that MA strategies become less profitable when used in high-frequency trading than when using their underlying indices.

The developments of Petrov S. and his colleagues in the field of applying digital technologies for modeling stock prices based on time-varying Walrasian equilibrium during exchange processes in the financial market are of interest (Petrov et al., 2021). The authors developed an econometric methodology for estimating the parameters of a certain quantity, which the authors called "instantaneous aggregate net demand". The author's development was based on a Walrasian equilibrium concept approach. Simultaneously, the concept demonstrated the behavior of the modeled stock price, which corresponded to the observed stock price for the Russian financial market.

Studying the integration of data mining methods, Sushkov et al. (2023) proposed using the approach he developed to identify fraud in financial control processes. The authors applied clustering methods, and a separate class of suspicious transactions was successfully identified, indicating the effectiveness of the proposed approach. Many factors should be considered for the formation and effective use of a cyber-physical system in the stock exchange sector, as studies have shown.

Nadezhda Yashina and her colleagues used digital methods of technical analysis to diagnose crisis phenomena in the Russian financial market to identify the development prospects of stock and financial markets. Researchers have developed tools for the technical analysis of financial assets to improve investment strategies during periods of crisis while widely using mathematical statistics, volatility indicators, and techniques to optimize portfolio investment management strategies (Yashina et al., 2022). The authors note that modern digital technologies can significantly reduce the time required to perform exchange transactions, for example, to milliseconds. However, despite the trading robot's speed, which can perform up to several hundred operations per second, it does not always provide a positive result. Therefore, despite significant scientific developments in this area, only a few algorithms have achieved a positive result.

According to Berawi, the management of AI technologies for creating added value is of great importance. Examples of disruptive innovations include the use of artificial intelligence, the application of the Internet of Things, machine learning, and big data. They allow for the digitalization, automation, or integration of SVCs (Berawi, 2020).

2. Methods

Many authors have written about the application of AI in the financial sector (Aruna and Rajat, 2024; Biswas et al., 2024; Stephan, 2023). The study found that AI has a significant impact on several areas of the financial sector, including algorithmic trading, fraud detection, customer service using chatbots, cybersecurity, and accounting. AI improves predictive analysis, service quality, enables fast and automated decision-making, and provides real-time customer information.

The rapid development of cyber-physical systems Artificial intelligence systems have become widespread in modeling the processes of various complex systems (Siripath et al., 2024), (Whulanza et al., 2024), (Shkarupeta et al., 2024), Chuen et al., (2024), (Villaverde and Maneetham, 2024).

The stated goal can be achieved using artificial intelligence-based methods. The following methods were used in this study: the random forest deep learning method, the fuzzy model, the popular Python library for machine learning Scikit-learn, which provides interaction with the Python NumPy and SciPy numerical and scientific libraries, and monographic and analytical methods. In practice, it is important to get a stable profit, both in a volatile market and in a practically motionless one—in a flat. DL-model "Random Forest" as the part of Hybrid Cyber-Physical System_en_SiU4_RFRegressor were designer at Colab. The Lua programming language was used as part of the Lua socket to develop the stock exchange bot.

The authors applied their developed approaches based on training an AI system, including optimizing the moment of activation of a robot for placing orders, formed using the fuzzy algorithm method.

Among the specific features of the Random Forest deep learning model that contribute to its accuracy in predicting stock prices, the following can be highlighted: 1) the model can work with small-sized datasets and does not retrain; 2) the random nature of the selection of factors in each of the decision trees allows you to make an optimal choice from a wide variety of intermediate options; and 3) a wide range of hyperparameter settings when forming models.

Algorithmic trading based on neural network forecast signals allows for positive profit. However, the trading result can be improved using signals from the fuzz algorithm in the interval between minute time frames (Figure 1).

Algorithmic trading based on the neural network's predictive signals allows you to get a positive profit. However, the trading result can be improved using signals from the fuzzy algorithm in the interval between minute time frames (Figure 1).

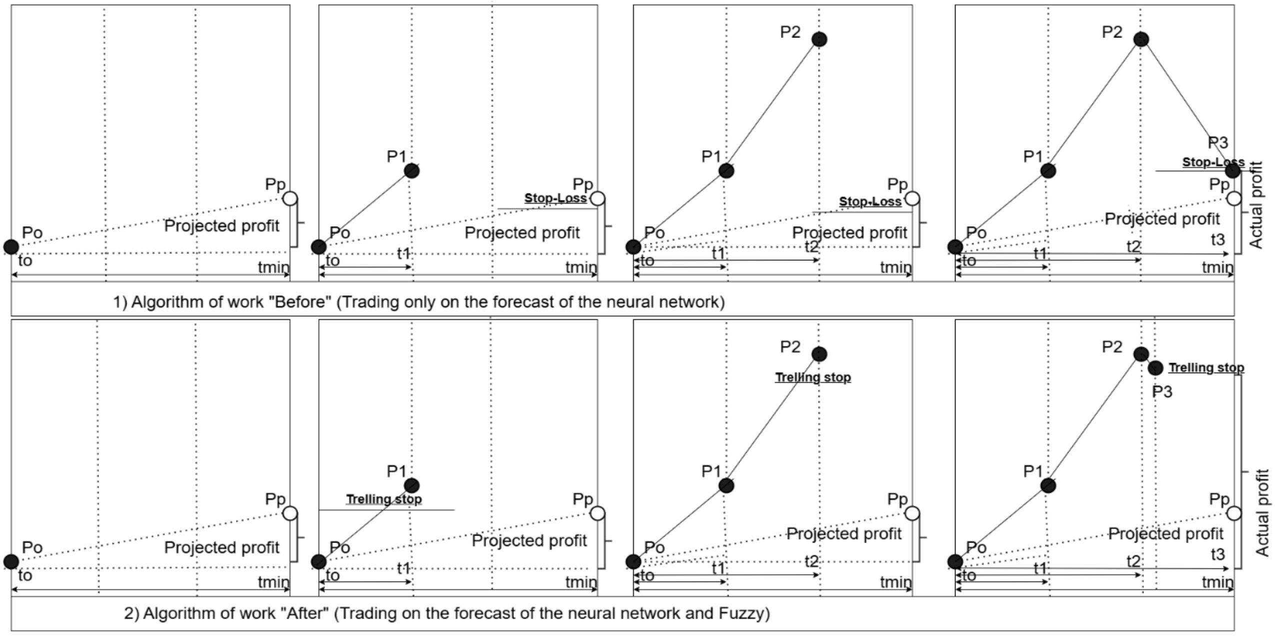

Figure 1 Algorithm of work "Before" and "After" the HCPS "Trading bot"

The top row of "frames" illustrates the trading robot's operation using only predictive values from the neural network - "Before". Upon receiving a predictive value in a growing market. The bot opens a long position and trades in the cycle mode "from the beginning of the minute until the end of this very minute". The asset price grows and overcomes the Pp mark, while a stop order is placed (by the amount of slippage, slightly below the predicted price value). In this mode of operation, the bot will not react in any way even if the price increases sharply due to volatility. It will only close the open Long position at the actual closing price of the "Pk" candle. After the minute interval has expired, the robot will earn a positive "actual profit".

The robot's performance can be improved if signals from both the neural network and the fuzzy algorithm are used within a 1-minute interval. Thus, when the conditions for triggering a purchase are met from both the neural network (Delta (PP-PK)> 50) and Fuzzy, on a growing market and Type/Offer> 3, the robot places a Long order and immediately a Trailing Stop with an offset from P1 by the amount of slippage. If the price suddenly rises sharply, the bot will also quickly raise the Trailing Stop to P2. Ultimately, the price will begin to fall, and the P3 level will trigger the Trailing Stop. As a result, you will receive an actual profit, the value of which is greater than that in the first case "Before".

Note that the system operates in a cycle until the end of trading on the line market. The parameters of the trailing stop offsets and the time between the trailing stops can be quickly adjusted. No orders are placed if the market is calm and the price forecast exceeds the actual price by less than 50 price points. In a falling market, the algorithm works in the reverse.

The essence of the method of integrating Fuzzy with a deep learning (DL) neural network to improve the overall trading strategy is that DL forms a price forecast based on historical candlestick and volume data, while Fuzzy makes a decision based on fresh Bid/Ask supply and demand data (from the trading order book), as well as the Delta parameter, which is calculated as the difference between the actual and forecast prices. The operation of this system of models can be improved in the future.

In the process of developing and implementing a hybrid cyber-physical system in real trading scenarios, the authors encountered several problems, in particular: 1) choosing an instrument (the prototype works with one C&C4 but many can be made, with a jump to more volatile ones); 2) choosing a concept for placing system modules (all modules should be transferred to the cloud, placed on the exchange server, although this is expensive); 3) selecting parameters in the trading robot settings, for example, the maximum size of the Delta parameter, the interval of the stop-loss indent from the price of the placed order, and others.

3. Results and Discussion

3.1. Neural Network Trading Bot as a Hybrid Cyber-Physical System

There are some opinions that NNs are not ideal when used. Deep learning models, such as Random Forest, can be unreliable due to their complexity and opacity, resulting in unforeseen trading risks.

These fears are exaggerated. If something goes wrong with the bot, it can automatically switch off owing to the risk module, for example, if the amount of losses reaches a predetermined value.

Trading bots can increase market volatility, which can harm the overall financial market stability. Robots have already "captured" all markets, but the world financial markets continue to operate. Moreover, the high profitability of trading bots makes them attractive for traders because their use provides very high profitability. Robots are starting to fight each other, and experts note facts of market manipulation due to the "swarm" effect (when a huge number of traders trade on signals "from the center" the swarm follows the queen bee), the "hummingbird" effect (when millisecond speed can bring many millions of dollars per year in arbitrage). Black swan news events usually disrupt the stability of the stock market (for example, the 2008 crisis and others). Neural network robots should not be feared.

The widespread use of such trading technologies may lead to unfair advantages for those with advanced technical skills, leaving some traders at a disadvantage. This thesis should not be refuted. To become a loser is the fate of traders who work "old-timers". Competition has always been and will continue to be. The world is cruel, but we must develop, learn, and apply modern technologies. There are many interesting developments that can turn the creation of trading robots into an attractive business.

The main modules presented in the HCPS "Trading bot" (see Figure 2).

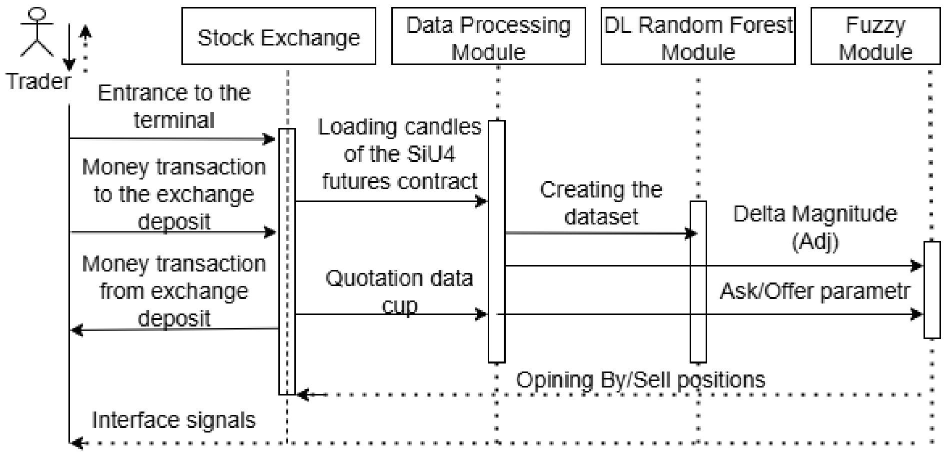

Figure 2 Structure of the hybrid cyber-physical system "Trading bot"

The developed hybrid cyber-physical system responds to changing parameters and performs the following functions:

- generates a dataset on a minute timeframe, which includes a five-dimensional vector (Popen, Phigh, Plow, Pclose, Volume) with a dimension of 5 x 3500;
- Importing a file from the disk space into the NN module (DL RF);
- The DL regression algorithm "Random Forest" calculates the predicted values of the closing price of the SiU4 futures using a five-dimensional vector that allows to automatically substitute values into the regression equation obtained using the Random Forest regression algorithm.
- The calculated regression coefficients are transferred to the decision-making module in the QUIK trading terminal.

The use of unified modeling language (UML) allows the use of graphical description for object modeling in the field of software development for modeling business processes. The diagram of the trading bot's uml objects is presented below (Figure 3).

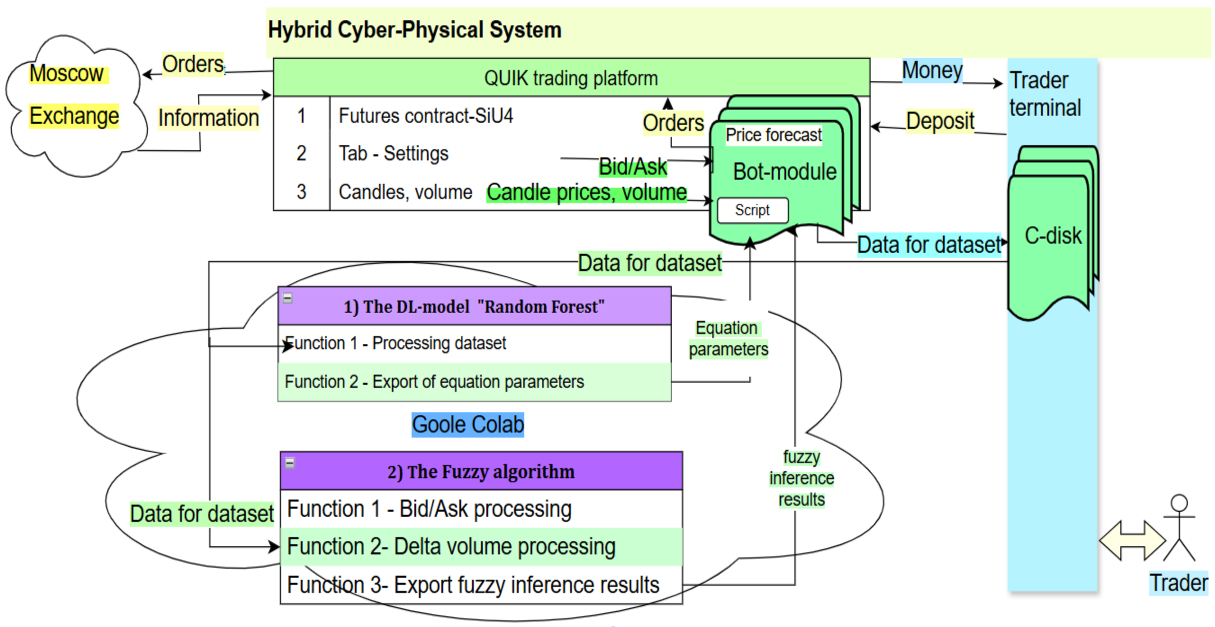

Figure 3 The diagram of the trading bot's UML objects

Below is a dataset containing candlestick and volume parameters for training the DL DL neural network. DL will forecast the closing price of the SIU4 futures. Below is a fragment of the dataset, with several lines, in which you can see the first 4 and last 2 lines, separated by ellipses (Table 1).

Table 1 Dataset for training the DL neural network (fragment)

Time	Open	*High*	*Low*	*Close*	*Volume*
10.01.00	879.040	879.190	878.700	878.770	2231.0
10.02.00	878.960	880.670	878.000	879.000	7925.0
10.03.00	879.670	879.770	878.610	879.010	14350.0
13.04.00	878.400	879.800	878.000	879.660	20926.0
…	….	….	….	….	….
22.44.00	820.000	821.000	820.000	820.140	4.0
23.45.00	821.390	821.390	821.390	821.390	1.0

Every minute, the program adds the Delta price and bid/ask values to this file, which are used to train the fuzzy algorithm. The interaction process between a trader and a stock trading bot installed on a personal computer ensures the integration of the HCPS modules into the trading process. An example of the organization of a hybrid simulation process in HCPS in a polymorphic mode is shown in Figure 4.

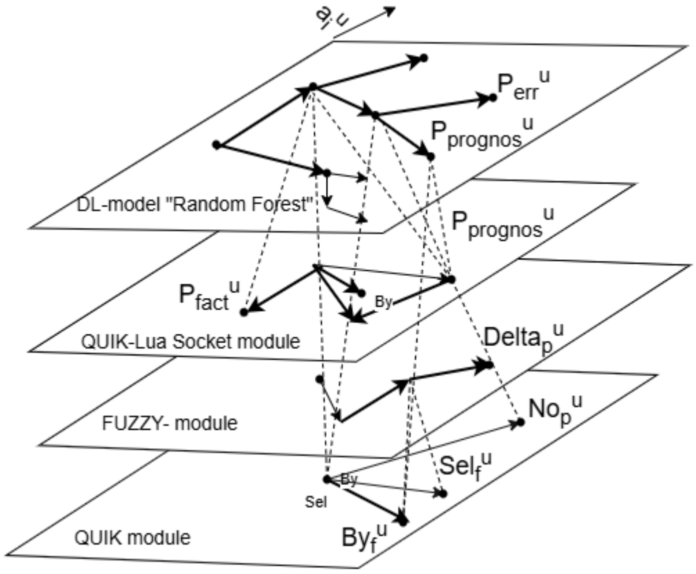

Figure 4 Hybrid Cyber-Physical System with a Fuzzy-module

The neural network DL-model "Random Forest" generates a forecast value of the closing price of the SiU4 futures contract's exchange asset. During GKFS operation, the trading bot performs many functions. These functions can be divided into the following categories: primitive, optimization, and cognitive. Primitive ones ensure the system's functioning: starting and stopping by time, restoring the connection to the exchange server in the event of a connection failure and other problems.

Optimization is associated with periodic retraining on fresh data. It has been experimentally established that the last 1000 candles on a minute time frame is the optimal use. In addition, some other parameters that can really affect the profitability of the bot can be changed. For example, the selection of the interval for setting a stop loss from the current price plays an important role.

Cognitive functions are related to searching and sorting through combinations of factors to retrain the DL model (this will be added in the future). Running the model during the testing and validation period revealed several major and minor problems in the prototype. For example, many parameters required adjustment by trial and error. In particular, the distance from the last trade price and the stop loss are designed to ensure reliable operation to close the position and minimize losses.

3.2. The "Random Forest" model

The data contained in the dataset were randomly divided into training and test sets at the next stage of the RF model formation. For this purpose, the train_test_split method, which is contained in the scikit-learn model_selection library, was used, while the share of the test fragment is usually 20%. The GridSearchCV library is used to set the desired RFM hyperparameters.

The GridSearchCV method functions are used to set the parameter combinations, which allow you to select the best option by enumerating all combinations. The following hyperparameters were used in the process of creating the model: the number of trees, 5, 10, and 50; the three criteria "squared_error", "absolute_error", "poisson", as well as the maximum tree depth, 2, 5, and 20.

Then, using the gs.best_estimator function, the best tree was selected from the entire set of trees generated by the algorithm. The best tree was characterized by the minimal error values "absolute_error", "max_depth", and had a maximum depth of 15 levels. A visualization of the best tree is shown below (see Figure 5).

The accuracy of the forecast is important because more accurate forecasts of the price of the exchange asset for each time interval are needed for effective trading. It is advisable to compare the forecasting quality with different hyperparameter settings of the DL RF model (Table 2).

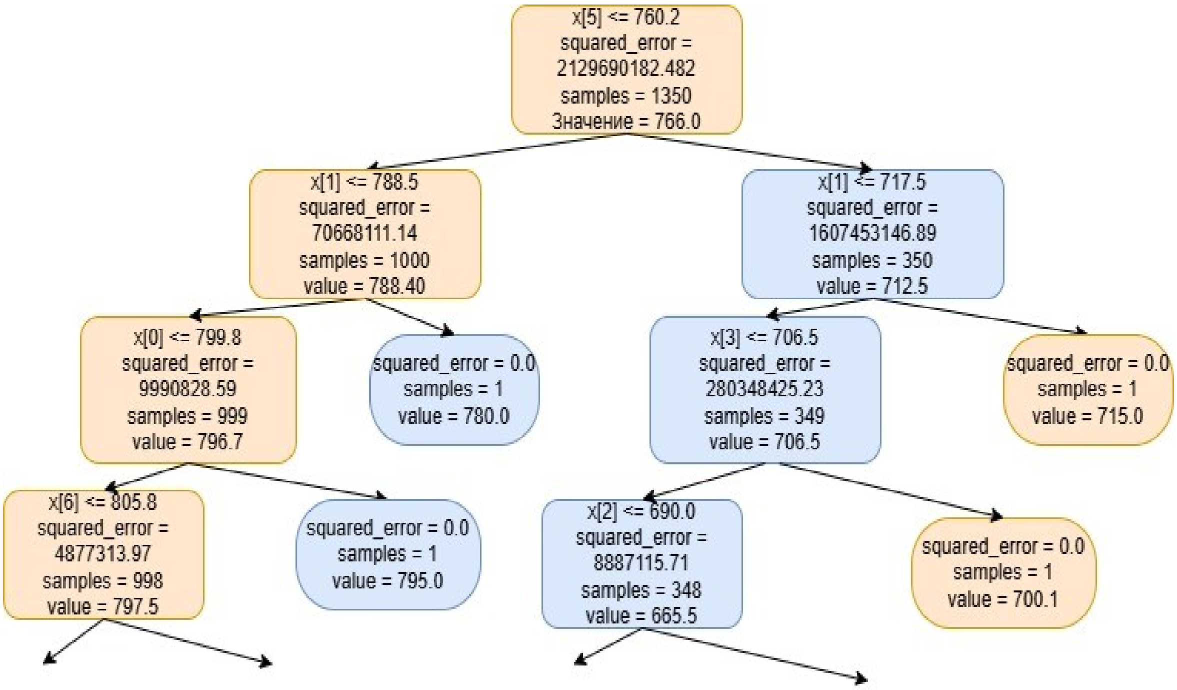

Figure 5 Visualization of the best tree of the "Random Forest" method (fragment)

Table 2 Comparative accuracy of forecasting using the DL models

Name	Value, dollars
MAE	0.9495
MSE	90.155
RMSE	0.94950

The neural network with the test sample share test_size = 0.20 shows a negligible forecast error. One of the factors of the trading bot's high efficiency is the low error in forming the asset price forecast. For example, the average absolute error of the MSE does not exceed USD 0.9495 or 0.11 percent.

3.3. Fuzzy Algorithm in Trading Bot

How the Fuzzy Algorithm works. The fuzzy algorithm transmits the generated "rules" (in the format "if ... then ...") to the trading bot. The "rules" are embedded in the trading bot script before launch and work successfully. The fuzzy algorithm ensures fast operation of the bot, which "without thinking", almost instantly, places long or short orders, and simultaneously places a stop loss at some distance from the price of the last transaction.

Correct settings allow you to "earn" on sharp price movements without allowing deposit drawdowns. The formed exchange bot has broad prospects for further functionality expansion. For the fuzzy algorithm to work, it must be trained.

The input data that the fuzzy module takes from the dataset are the Delta and Bid/Ask parameters for each minute. The algorithm is trained in the Kolab service using standard libraries. The libraries perform fuzzification, rule building, and defuzzification functions. At the output, the trained algorithm will issue a signal: "1" - to buy an asset (opening a long Long position), or "-1" (to open a short Short position). At the same time, the bot places a corresponding order in the QUICK system.

It is important to know the origin of the Delta and Bid/Ask parameters. There is a special function in the bot script that calculates the delta parameter. Using the forecast value of the closing price for the next timeframe and the actual price at a given point in time, the function calculates the Delta parameter as the difference between the forecast and the actual price.

To calculate the bid/ask parameter at each time point,

Information reflecting supply and demand comes from the order book. The bot script function instantly multiplies the number of orders in the order book by the prices from both sellers and buyers, sums up the resulting products, and then finds their ratio: calculating the Bid/Ask index.

Thus, during operation, the Delta and Bid/Ask parameters are used to make trading decisions. These parameters are recorded in the dataset, which is then used to retrain the model on fresh data.

Because the bot interface is integrated into the QUIK trading terminal, the necessary information in the form of messages appears during the trading bot's operation. For example, the predicted values of the instrument's closing price are regularly calculated.

The DL RF transmits the linear multifactor regression formula to the decision module (Equation 5):

$$Pp = a \;\; b*O + c*H \;\; d*L + f*C \;\; i*V, \tag{5}$$

Here, a is the free term, and b, c, d, and i are the regression equation coefficients (Open, High, Low, Close, and Volume, respectively). The decision module is written in the LUA. The module performs many functions, such as the following:

- Connecting to the QUIK terminal
- receiving quotes for a financial instrument (SiU4); and
- calculating the regression equation based on the data of the last candle;
- Analysis of values and decision-making on buying/selling a stock exchange asset;
- Starting and stopping on demand;
- Restoring a broken connection with the exchange server.

A problem arose when forecasting in a flat DL-RF model, despite the forecast accuracy

The intra-candle price movement often goes against the forecast.

It is advisable to use the fuzzy algorithm to make a decision on buying/selling an exchange asset in the conditions of uncertainty of the intra-minute timeframe, the input parameters of which were chosen: Bid/Offer and Delta. Bid/Offer is the ratio of the volumes of orders for sale/purchase and is calculated in real time based on data from the exchange order book. The delta is the difference between the forecast price and the actual closing price. Both parameters are in constant motion, reflecting the market’s state and mood at a specific point in time.

The dynamics of the Delta (Pp-Pc) and Bid/Offer parameters for the formation of the fuzzy algorithm are presented in Table 3.

Table 3 Delta (Pp-Pc) and Bid/Offer dynamics

Name	Delta (Pp-Pc), rubles	Bid/Offer
Max	73	8.61
Min	10	0.71
Range of variation	63	7.9
Average	44.4	4.8
Number of values (N)	11	11
1st interval	10-31	0.71–3.34
2nd interval	32-53	3.35–5.98
3rd interval	54-73	5.99–8.61

The fuzzy algorithm works in such a way that several stages occur: gasification, formation of fuzzy rules for the inference system, and defuzzification. It seems appropriate to perform gasification (Table 4).

Table 4 Introduction of fuzziness (phasification)

	Delta (Pp-Pc), rubles	Bid/Offer	Signal
Linguistic designation	poor optimal unreliable	low medium high	Sell Buy Buy

The visualization of fuzzy logical inference was successfully obtained based on the application of fuzzy rules. Fuzzy rules and fuzzy inference (Figure 6).

After the order placed in the trading system is processed and is visible as an open position, for example, long), the Exchange Bot system will automatically place a stop-loss order below the actual market price at a certain distance, for example, 0.1 USD).

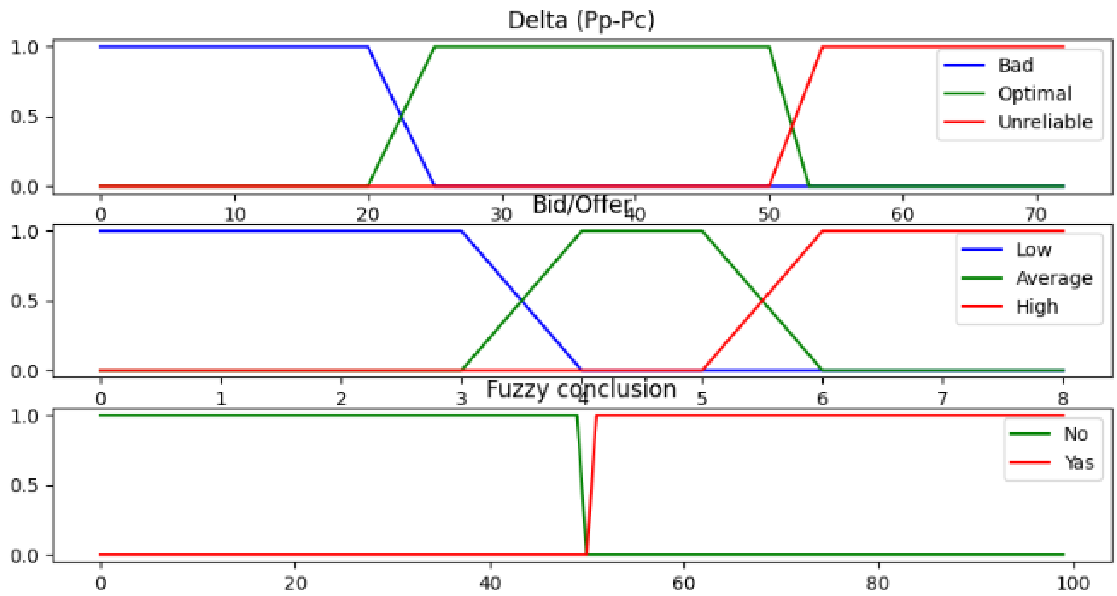

Figure 6 The visualization of fuzzy logical inference

When the market price moves, for example, upwards, the bot algorithm is designed to move the stop loss following the market price to reduce the gap between the changed price and the set stop, which will reduce financial losses and help increase the effectiveness of trading with each price change greater than a certain specified value. The open position is not closed until the market price moves down and the stop-loss is triggered, closing the position. The process continues in a cycle, and the stop-loss location is checked every second. The process is similar, but mirrored, if the order was placed "short". The efficiency of using the fuzzy algorithm is presented in Table 6. Using the Delta (Pp-Pc) and Bid/Offer signals in the fuzzy algorithm enables the system to correctly place an order and make a profit, in our case 2.10 dollars of positive margin, instead of 1.61 dollars of negative margin, in 11 minutes (Table 5).

Table 5 Efficiency of using the fuzzy algorithm

Time	*Pc*	*Pp*	*Delta (Pp-Pc)*	*Bid/ Offer*	*ΔPc (t+1)*	Signal Long	Margin Fuzzy Pc(t2-1)	Margin DL RF (Pp-Pc)
29.07.2024 12.24:00	872.95	873.45	0.50	5.25	0.00	1	-	-
29.07.2024 12.25:00	873.15	873.61	0.46	7.12	0.20	1	0.20	0.20
29.07.2024 12.26:00	873.19	873.61	0.42	6.12	0.04	1	0.04	0.04
29.07.2024 12.27:00	873.28	873.65	0.37	6.62	0.09	-1	0.09	0.09
29.07.2024 12.28:00	873.22	873.55	0.33	2.19	-0.06	-1	0.06	-0.06
29.07.2024 12.29:00	872.95	873.68	0.73	6.55	-0.27	-1	0.27	-0.27
29.07.2024 12.30:00	872.95	873.37	0.42	7.7	0.00	-1	0.00	0.00
29.07.2024 12.31:00	872.78	873.28	0.50	0.8	-0.17	-1	0.17	-0.17
29.07.2024 12.32:00	871.92	872.40	0.48	0.75	-0.86	1	0.86	-0.86
29.07.2024 12.33:00	872.07	872.64	0.57	8.61	0.15	-1	0.15	0.15
29.07.2024 12.33:00	871.81	871.91	0.10	0.71	-0.26	-	0.26	-0.73
Max			0.73	8.61	0.20			
Min			0.10	0.71	-0.86			
Range of variation			0.63	7.9				
Sum							2.10	-1.61

Earlier developments by the author were reflected in the Certificate of Registration of the computer program 2022662398 dated 04.07.2022 "Exchange trading Quik-bot" (Lomakin, 2022) and others, for example (Naidenko et al., 2019). The formed exchange bot has potential for expanding its functionality. The trading bot code fragment in the Lua language is presented below (Figure 7).

To ensure interaction of the bot script in Lua with the QUIK terminal, the terminal has a Lua interpreter called QLua. It represents a set of functions, and certain actions occur when called. The QLua interpreter functions can be called with certain parameters for successful interaction. In this case, depending on the parameters specified during the call, a certain action is performed or certain values are returned. All available QLua interpreter functions are presented in detail in the Lua language documentation in QUIK. Callback functions are significant. These functions are processed in the QUIK terminal's main thread.

```
progname="example_one: "
  do_it = true
end
function OnStop() -- Function to stop the bot program
  do_it = false
  message(progname.." bot termination ")
end
function main() -- The main function in which the sequential execution of the

     sleep(1000) - Command to pause the program in
milliseconds
    end
end
```

Figure 7 Fragment of trading bot code in Lua language

The user can optimize the execution time of such functions if necessary. The manner in which they are designated and what they do is shown in Table 6 below. Using the existing functions provides ample opportunities for further development of the exchange bot as a hybrid CP system.

Regarding future research on the topic, we can highlight three areas that are most important. First, it is important to study and identify the factors that influence stock asset prices' behavior. The study by Deng and colleagues, who identified hidden factors that influenced changes in stock asset prices (Deng et al., 2023), was very productive, as was the study by Franklin et al. (2019), which was devoted to pricing processes in financial markets, taking into account the fundamental and information risks that shape the stock market reaction (Franklin et al., 2019).

Table 6 List of callback functions performed in the QLua program (fragment)

Designation	The nature of the function performed
main	implementation of the main execution flow in the script
OnAccountBalance	change of position on the account
OnAccountPosition	change of position on the account
OnAllTrade	new impersonal transaction
OnCleanUp	change of trading session
OnClose	close of QUIK terminal or unloading of file qlua.dll
OnConnected	establishing connection with QUIK server
OnDepoLimit	change of position on instruments
OnDepoLimitDelete	deletion of position on instruments
OnDisconnected	disconnection from QUIK server

Second, methods and approaches for monitoring and reducing financial risk in exchange algorithmic trading are studied. Of scientific interest is the study of Fama and MacBeth, who found it necessary to consider risk as a category in which profitability and equilibrium are observed (Fama and MacBeth, 2025).

Third, methods for improving exchange cyber-physical systems are studied. The DL model and fuzzy model are algorithms that, together with other models and methods, formed the basis of the study. Obtaining new knowledge about the market and forming experience based on the triad: subject of activity, task, and circumstances, as proposed by the scientist Shvedin, can be a promising direction to make a trading bot capable of analyzing and remembering a situation and information about it, so that in the future, based on the identified dependencies and patterns, it can properly restructure its work to work more efficiently and profitably (Shvedin, 2021). The use of AI systems, as practice shows, makes it possible to solve several problems in financial markets and stock trading.

The use of AI-based cyber-physical systems has great potential in the financial sector and many related areas. This is confirmed by the following studies: Chen et al. (2024), Cao et al. (2024), Lu and Yang (2024), Kuang et al. (2024), Chishti et al. (2024), Zeng and Zhang (2024), Šeho et al., (2024), Meng et al. (2024).

Ruiz-Vanoye and co-authors presented a comprehensive review of industrial robots based on Howard Gardner's theory of multiple intelligences. Based on Gardner's intellectual framework, the authors classified various AI capabilities, such as visual recognition, decision making, and collaborative interaction, to provide a new taxonomy that can bridge human cognitive abilities with artificial systems (Ruiz-Vanoye et al., 2024).

4. Conclusions

As a result of the study, a stock exchange trading bot was formed, which is a hybrid cyber-physical system based on the DL RF artificial intelligence system for forecasting and the fuzzy module for trading. DL RF is designed to calculate the forecast price of an exchange asset based on the following prices: opening, maximum, minimum, and closing, as well as the volume for the next timeframe. The fuzzy algorithm can make a decision on placing a long or short position based on fuzzy choice to achieve effective profitable trading based on changes in the values: Delta, the difference between the forecast price value and the actual price, and the bid/offer coefficient, which reflects the ratio of purchase/sale requests in the exchange order book. As a result, a DL model of the RF AI system was formed. A fuzzy algorithm was formed to make a buying/selling decision based on the obtained forecast price. Promising areas for further research may be: the use of large data sets due to an increase in the frequency of observations and the use of deep neural networks LSTP, which allow the features of time frames to be considered when constructing a forecast.

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Author Contributions

Authors' contributions: Nikolay Lomakin, Skhvediani Angi and Alena Kuzmina designed the experiment. Tatyana Boriskina, Elena Samsonova and Ekaterina Kosobokova collected and processed the input data. Alexey Kizim and Ivan Lomakin wrote the code, ran the model, and analyzed the output data. Nikolay Lomakin supervised the experiment and wrote the manuscript. All authors contributed equally to the work, the results of which are presented in this paper.

Conflict of Interest

The authors declare no conflicts of interest.

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