Adaptive neuro-fuzzy inference system (ANFIS) it is a type of neural network that combines the strengths of both fuzzy logic and artificial neural networks. ANFIS is particularly useful in stock trading because it can handle uncertainty and imprecision in the data, which is common in stock market data. In stock trading, ANFIS can be used for a variety of purposes, such as predicting stock prices, identifying profitable trades, and detecting stock market trends. One of the key advantages of using ANFIS for stock trading is that it can handle both linear and non-linear relationships in the data. This is particularly useful in the stock market, where the relationships between different variables are often complex and non-linear. ANFIS can also be updated and retrained as new data becomes available, which allows it to adapt to changing market conditions. Therefore, the main hypothesis of this work is to understand whether it is possible to predict the dynamics of prices for stocks of companies in the electric vehicle (EV) sector using technical analysis indicators. The purpose of this work is to create a model for predicting the prices of companies in the EV sector. The technical analysis indicators were processed by several machine learning models. Linear models generally perform worse than more advanced techniques. Decision trees, whether fine or coarse, tend to yield poorer performance results in terms of RMSE, MSE and MAE. After conducting a data analysis, the ANFIS and Bayesian regularization back propagation Neural Network (BR-BPNN) models were seen to be the most effective. The ANFIS was trained for 2000 epochs which yielded a minimum RMSE of 5.90926

Keywords: stock price forecasting, correlation of technical indicators, neural network, adaptive neuro-fuzzy inference system, electric vehicle sector

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DEVELOPMENT NEURO-FUZZY MODEL TO PREDICT THE STOCKS OF COMPANIES IN THE ELECTRIC VEHICLE INDUSTRY

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1 Introduction

Each state sets itself a strategic goal to improve and strengthen its economy. A strong economy will provide citizens with a good standard of living by increasing government spending on social programs. In order to keep up with the rapid changes in the world economy and to have great economic opportunities, modern states encourage the creation of large corporations. These corporations primarily list their shares in stock markets, which are a collection of securities traded between market participants. The EV industry has witnessed significant growth and transformation in recent years, driven by advancements in technology, environmental concerns, and increasing demand for sustainable transportation alternatives. As this industry continues to expand, investors and stakeholders seek accurate and reliable methods to predict stock prices and make informed decisions regarding their investments. In the financial world, stock prediction models play a crucial role in analyzing market trends and forecasting future stock prices. Traditional models, such as fundamental and technical analysis, have long been employed for this purpose. However, these methods often struggle to capture the intricate relationships and dynamic nature of the EV industry, which is influenced by a wide range of factors including technological advancements, government policies, consumer preferences, and global market dynamics. To address the limitations of traditional approaches, researchers and analysts have turned to advanced computational techniques that can leverage vast amounts of data and extract meaningful patterns and relationships. In recent years, neuro-fuzzy models have emerged as a promising tool for stock price prediction due to their ability to integrate the strengths of artificial neural networks (ANNs) and fuzzy logic systems. Neuro-fuzzy models combine the learning capabilities of ANNs with the interpretability and linguistic rules of fuzzy logic, providing a robust framework for capturing complex patterns in financial data. By integrating historical stock prices, EV industry-specific indicators, and relevant macroeconomic factors, a neuro-fuzzy model can learn from past trends and generate accurate predictions regarding the future performance of companies operating in the electric vehicle sector.

Accurate predictions of stock prices can enable investors to make more informed decisions, optimize their portfolios, and manage risk effectively in the highly competitive and volatile EV market. Therefore, studies that are devoted to use of neuro-fuzzy models for predicting stock prices are has scientific relevance.

2. Literature review and problem statement

In paper [1] proposed a new approach for predicting stock price movements. The primary problem addressed in the paper is the prediction of stock price movements. Accurately predicting stock prices is a challenging task due to the complex and dynamic nature of financial markets. Stock prices are influenced by various factors such as market sentiment, economic indicators, company news, and global events. Traditional approaches to stock price prediction often rely on single-source data or limited features, which may not capture the full complexity of the market dynamics. To overcome these limitations, the authors propose a multi-source aggregated classification framework that leverages multiple sources of information to predict stock price movements. The framework integrates textual data from financial news articles and numerical data from financial statements to capture both qualitative and quantitative aspects of stock market behavior. By combining multiple sources of information, the proposed approach aims to improve the accuracy and robustness of stock price predictions. Another problem addressed in the paper is feature selection and representation. The authors highlight that selecting relevant features and representing them effectively are crucial for accurate stock price prediction. In this regard, they propose a feature selection method based on mutual information to identify informative features from financial news articles. Additionally, they employ word embedding techniques to represent textual data in a continuous vector space, enabling better integration with numerical data. This article poorly addresses the problem of handling imbalanced datasets when predicting stock prices. To mitigate this problem, the authors propose a cost-aware learning approach that assigns different misclassification costs to different classes, thereby improving the prediction performance for the minority class. But still, some classes (for example, positive or negative price movement) significantly prevail over other classes. This imbalance leads to biased forecasts and reduced performance. This paper explores the use of these methods in predicting stock market indices and the direction of stock price index movement [2]. The authors of this research highlight the importance of accurate forecasting of stock market trends for investors and traders. One of the main problems addressed in this paper is the inherent complexity and volatility of the stock market. The stock market is influenced by a wide range of factors, including economic indicators, political events, company performance, investor sentiment, and global market trends. These factors interact in complex ways, making it challenging to accurately predict future stock prices. Traditional statistical models often struggle to capture the nonlinear relationships and complex patterns present in stock market data. Deep learning and machine learning algorithms offer a promising solution to this problem. These techniques can automatically learn from large amounts of historical data and identify hidden patterns that may not be apparent to human analysts. However, there are several challenges associated with applying deep learning and machine learning to stock market forecasting. One major challenge is the availability and quality of data. Stock market data is often noisy, incomplete, and subject to various biases. Obtaining reliable and comprehensive data is crucial for training accurate prediction models. Authors in this study [3] use various time series models, including ARIMA, SARIMA, and LSTM, to predict the close price of stocks in the Saudi stock exchange. One of the main issues with this paper is the limited scope of analysis. The authors only focus on predicting the close price, neglecting other important factors that can influence stock prices, such as trading volume, market sentiment, and macroeconomic indicators. By solely relying on time series models, the paper fails to capture the complex dynamics and interdependencies that exist in financial markets. Authors of this paper [4] use a knowledge graph-based event embedding framework to represent textual and relational data related to the stock market. The paper addresses several problems in stock movement prediction with textual and relational data. These problems include the effective utilization of unstructured textual data, capturing temporal dependencies in stock movements, and filtering out noise and irrelevant information. The proposed graph-based learning framework, along with the temporal graph convolutional network and attention mechanisms, aims to overcome these challenges and improve the accuracy of stock movement predictions. The state of the economy, political events, the behavioral psychology of traders and many other factors affect the reliability of forecasts. In this research proposed approach for forecasting the price of nickel using a Long Short-Term Memory (LSTM) neural network optimized by the improved Particle Swarm Optimization (PSO) algorithm [5]. Paper-based forecasting models suffer from several limitations, including manual data analysis, lack of adaptability, and limited transparency. The application of advanced computational techniques such as LSTM neural networks optimized by algorithms like PSO offers a potential solution to these problems. By leveraging the power of AI and ML, these models can automate the forecasting process, improve accuracy, and enable real-time updates. However, it is important to note that the effectiveness of these techniques may vary depending on the specific domain and dataset. In this study authors use machine learning methods to predict the prices of biomass based on historical data [6]. This study highlights several problems associated with biomass pricing in Poland. These include the lack of standardized pricing mechanisms, the variability of biomass quality and composition, and the influence of external factors on prices. The proposed predictive model offers a potential solution to improve price forecasting and decision-making in the biomass market. This article [7] investigates the impact of external shocks on the prices of Malaysian crude palm oil using a Structural Vector Autoregressive (SVAR) model. In this paper authors use a new stock crisis prediction method that combines machine learning and statistical models to predict stock market crises [8]. To achieve their research objectives, the authors propose a new method for predicting stock crises in the Pakistan stock market. They utilize a combination of technical analysis indicators and machine learning algorithms to develop a predictive model. The technical analysis indicators used include moving averages, relative strength index (RSI), and stochastic oscillator. These indicators are commonly used in financial analysis to identify trends and potential turning points in stock prices. Many researchers try to solve the problem of price prediction using machine learning methods, probabilistic models, evolutionary algorithms. In this paper [9] investigated intraday and interday features in high-frequency data in China's stock market before and after the financial crisis. The authors use a comprehensive set of features, including volatility, liquidity, and trading volume, to analyze the intraday and interday patterns in the stock market. One of the main problems addressed in the paper is the impact of financial crises on the intraday and interday features of high-frequency data. Financial crises can significantly disrupt market dynamics, leading to increased volatility, liquidity issues, and changes in trading patterns. The authors investigate how these crises affect the intraday and interday features of China's stock market, providing valuable insights into the behavior of market participants during such turbulent times. This study [10] proposes a new approach for forecasting stock prices and evaluating trading profits using a time series model based on deep learning and an integrated indicator selection method. The authors screen technical indicators as research variables from the literature review and transfer the four basic information (opening, highest, lowest, and closing price) of stock trading into the technical indicators. Researchers of this paper [11] propose a new approach for stock portfolio optimization using machine learning. The authors develop a machine learning model for detecting companies with lasting competitive advantages, also known as companies' moats, and use this information to optimize stock portfolios. In this research authors [12] develop method called Optimal Action Space Search (OASS) that optimizes the action space of the reinforcement learning agent to improve trading performance. Main challenge discussed in the research is the non-stationarity of financial markets. This non-stationarity poses a challenge for DRL algorithms, as they need to adapt and update their strategies in response to changing market dynamics. The authors propose a two-step training process to address this issue. In the first step, a pre-training phase is conducted using historical market data to initialize the value network. This helps the algorithm capture some general patterns and dependencies in the data. In the second step, an online training phase is performed using real-time market data. This allows the algorithm to adapt and update its strategies based on the current market conditions. This study [13] proposes a new approach for forecasting the Cboe Volatility Index (VIX) and its volatility using machine learning methods. The authors develop an intelligent probabilistic forecasting model that combines machine learning algorithms with probabilistic models to predict the VIX and its volatility. This research [14] proposes a new approach for connecting macroscopic time series forecasting with microscopic time series data using MixSeq. One key challenge of this research is the heterogeneity of the two types of data. Macroscopic data typically exhibit long-term trends and seasonality patterns, while microscopic data may contain irregular fluctuations and noise. Integrating these two types of data requires addressing the differences in their statistical properties and finding effective ways to combine them. Authors of this study [15] introduce linguistic variables with positive and negative symmetrical judgments to represent the direction of the stock market movement. The method is developed that combines fundamental and technical indicators with a self-adaptive evolutionary algorithm to optimize portfolio composition [16]. This research proposes an approach for stock price forecasting using a hybrid evolutionary intelligent system and hybrid time series econometric model [17]. The paper proposes a hybrid approach that combines evolutionary intelligent systems and time series econometric models for stock price forecasting. Evolutionary intelligent systems refer to computational techniques inspired by biological evolution and natural selection. These techniques include genetic algorithms, particle swarm optimization, and artificial neural networks. Time series econometric models, on the other hand, analyze historical data to identify patterns and trends in stock prices. The results of this article [18] show that the proposed approach for optimal portfolio management using nonconvex cardinality constraint outperforms other methods in terms of portfolio performance. In this paper [19] discusses the challenges and solutions related to portfolio management in engineering problems. The authors focus on the application of nonconvex cardinality constraints in optimizing portfolios, providing a computing perspective to address these issues. Among all the most famous artificial intelligence methods that allow to form predictive models, artificial neural networks are the most popular for solving these problems [20]. Authors of this study [21] develop method that combines the improved stochastic simulation algorithm (ISSA) with the backpropagation (BP) neural network to optimize the prediction accuracy of the stock market index. In this research authors [22] develop a new method that combines convolutional neural networks (CNNs) and long short-term memory (LSTM) to predict stock market prices. The proposed method is evaluated on real-world stock market data from Tesla and Apple. Among neural networks, there are models based on statistical and non-parametric methods [23]. The authors of this research [23] conducted a survey to identify the key issues faced in this domain and presented their findings in the paper. One of the main problems discussed in the paper is the high volatility and nonlinearity of stock market data. Stock prices are influenced by various factors such as economic indicators, political events, investor sentiment, and company-specific news. These factors can lead to sudden fluctuations in stock prices, making it difficult to accurately predict future trends. Additionally, stock market data often exhibits non-linear patterns, which further complicates the forecasting process. In the paper [24] introduced approach for modeling the Indonesian Composite Index using artificial neural network (ANN) and nonparametric MARS regression. In the paper [25] researchers investigates the predictability of machine learning techniques for forecasting the trends of market index prices in the Korean stock markets. The authors propose a forecasting model based on a neural network that can predict the price of a financial asset in a well-defined time interval. Ten technical indicators are used as input signals, and the closing price of the next period is used as an output signal. The paper highlights the advantages of artificial neural networks (ANNs) in comparison with other methods and models of forecasting. The authors reinterpreted the financial forecasting paradigm, using indicators as sources of basic market information and a continuous input classification model as the neural network architecture. The main goals in investing in the stock market are to increase profits and to minimize risk. The economic growth of the state correlates with the strengthening of the stock market [26]. Predicting the behavior of prices in the stock market is the best way to make a profit. Statistical models are inferior in predictive accuracy to conventional machine learning models [27]. The Gaussian Naïve Bayes algorithm assumes that the feature values follow a normal distribution. However, stock market data often exhibit non-normal distributions with skewness and heavy tails. This discrepancy between the assumed distribution and the actual distribution of feature values can affect the performance of the algorithm and lead to inaccurate predictions. Long short-term memory (LSTM) based deep learning models outperform machine learning models such as support vector regression (SVR) [28]. Also deep learning models based on neural networks show better performance than support vector machine (SVM) [29]. Deep learning models have shown good potential for use in stock market forecasting due to their ability to detect stock market dynamics and obtain adequate results [30].

The first electric car was built back in 1884 by Thomas Parker using high-capacity rechargeable batteries [31]. High cost, low top speed, and limited battery range have held back the industry.

All this allows to assert that it is expedient to conduct a study on forecasting the prices of shares of companies in the EV sector, which is of great importance for equity financing, risk identification, and policy formulation of EV enterprises.

3. The aim and objectives of the study

The aim of the study is to develop a model for predicting the dynamics of stock prices of companies in the electric vehicle sector using neural networks.

To achieve this aim, the following objectives are accomplished:

– to correlate the indicators of the electric vehicle sector statistical processing of technical analysis data will be carried out;

– to visualize information and make it easier to understand complex datasets, instead of simply listing numerical values or textual descriptions, a graphical representation of data will be used by different plot functions;

– to build a neuro-fuzzy forecasting model, an architecture of a fuzzy expert system will be built;

– to prove the performance of the model, a comparison of the obtained model with other known machine learning models will be carried out, and predictive experiments will also be carried out.

4. Materials and methods

4. 1. Object and hypothesis of the study

The object of the study is model to predict the stock prices or trends of companies operating in the electric vehicle (EV) industry.

The main hypothesis of the study: «An integrated neuro-fuzzy model, combining the strengths of artificial neural networks and fuzzy logic, can accurately predict the stock prices or trends of companies operating in the electric vehicle industry». This hypothesis suggests that by harnessing the power of neural networks to learn complex patterns from historical stock market data and using fuzzy logic to handle uncertainties and linguistic variables, the developed model will be able to make reliable predictions regarding the stock performance of companies within the electric vehicle sector. The study aims to demonstrate that this novel approach can outperform traditional prediction models and provide valuable insights for investors and stakeholders interested in the electric vehicle industry.

4. 2. Methods for calculating technical indicators

Technical analysis is used by financial experts to make decisions in the stock market. Analysts look for patterns, trends, and other factors that are present in financial stock market price data. The results of stock price movements can be effectively predicted using patterns and trends. These patterns and trends allow investors to make effective decisions to buy or sell securities. Price movement parameters are defined as indices that are calculated from existing historical data according to a certain type of reasoning, which is usually based on heuristics [32, 33]. Technical analysis has more predictive power than other statistical methods [34]. To eliminate the shortcomings of any technical analysis indicator, additional indicators are added: simple moving average (SMA), moving average convergence divergence (MACD), average directional index (ADX), relative strength index (RSI), Stochastic and others. In the case where the forecasting system consists of two, three or four indicators, it becomes more difficult to read all the signals without errors. Managing a system with several indicators is much more difficult than with one. But such systems show more objective patterns for traders to act on. Let's hope that the use of neural networks will allow to simplify the management of such a complex system. Thus, in this work, the following four technical indices are selected, which have a higher predictive power:

– the average share price for the last 50 days, calculated as the unweighted average of the previous 50 share closing prices (SMA50);

– convergence/divergence of moving averages (MACD);

– relative strength index (RSI);

– stochastic oscillator (SO).

SMA will always show lagging behind the real price. That is, the longer the period used for averaging, the greater the lag will be. In order for the SMA to change its course, a large price movement in the market is necessary. This is due to the large amount of historical data that is taken into account when calculating the long-term SMA. This indicator is one of the simplest and most effective ways to confirm the price trend. The SMA is calculated based on a time series of past events based on what has already happened, which is what makes the indicator such a good trend confirmation tool. Confirmation of the bullish trend is described by a clear rising SMA line. Conversely, if the line is in a downward movement, then this is a confirmation of the bearish trend [35, 36]. As this indicator, let's use the dynamics of this indicator in % terms with the current closing price. The calculation formula is as follows:

$$\text{Dynamic\_SMA50}=(\text{SMA50}-\text{Close})/\text{SMA50}*100.$$

MACD is a technical indicator developed by Gerald Appel used in technical analysis to assess and predict price fluctuations in the stock and currency markets. The indicator is used to check the strength and direction of the trend, as well as to determine the turning points based on moving averages. Usually, a «Buy» signal is considered when the MACD line crosses the signal line from the bottom up. The «Sell» signal is considered when the MACD line crosses the signal line from top to bottom. To calculate a linear MACD, an exponential moving average with a longer period is subtracted from the moving average price (usually an exponential moving average with a shorter period is taken). In most cases, the result is smoothed using an exponential moving average (EMA) to eliminate random fluctuations [37–40]:

$$\text{MACD}=\text{EMA}_s(P)-\text{EMA}_l(P), \quad (1)$$

$$\text{Signal}=\text{EMA}_a(\text{EMA}_s(P)-\text{EMA}_l(P)) \text{ (signal line)}, \quad (2)$$

$$\text{Difference histogram}=(1)-(2).$$

Here:

– $EMA_s(P)$ – exponential moving average with a short period from the price;

– $EMA_l(P)$ – exponential moving average with a long period from the price;

– $EMA_a(P)$ – a smoothing moving average with a short period of the difference between the other two moving averages;

– P – price, usually the closing price of the Close period is taken, but other options are also possible (Open, High, Low, Close, Median Price, Typical Price and others).

By default, the following MACD settings are often used on the daily chart:

– EMA_s – (short) with a period of 12 days (two weeks);

– EMA_l – (long) with a period of 26 days (month);

– EMA_a – (smoothing difference) with a period of 9 values.

The Relative Strength Index measures the speed and magnitude of an asset's price movements. The main task of RSI is to analyze the strength of price momentum and help in determining the level of overbought or oversold assets. RSI is depicted on the chart as an oscillator with a value from 0 to 100. The generally accepted overbought level of an asset is a zone above 70, oversold – below 30. The RSI indicator «weighs the forces» of rising and falling asset prices. The following formula is used to calculate RSI values: $RSI=100-100/(1+RS)$. RS is the exponential average of the price when the asset rose over the considered time period divided by the exponential average of the price when the asset fell over the considered time period [41, 42].

The stochastic oscillator shows the position of the current price relative to the price range for a certain period in the past. Measured in percentage. According to the interpretation of the author of the indicator, George Lane, the main idea is that with a rising price trend (uptrend), the closing price of the next timeframe tends to stop near the previous highs. With a downward price trend (falling trend), the closing price of the next timeframe tends to stop near previous lows. In fact, the indicator demonstrates the divergence of the closing price of the current period relative to the prices of previous periods within a given time period.

The most common interpretations of the stochastic oscillator chart: Buy when the indicator chart line (%K or %D) first falls below the agreed level (usually 20 %) and then rises above it. Sell when the indicator chart line first rises above a certain level (usually 80 %), and then falls below it. Buy if the %K line rises above the %D line. Sell if the %K line falls below the %D line. To identify divergences, for example, when prices form a series of new highs, and the stochastic indicator fails to rise above its previous highs, it is possible to expect the beginning of a downward trend in prices, that is, it is possible to sell. Crossing the 80 % mark with the growth of the indicator is interpreted as a signal of a likely stop in growth or even the beginning of a decline in prices. Crossing the 20 % mark when the indicator goes down is interpreted as a signal of a likely stop in the fall or even the beginning of an increase in prices [37].

4. 3. Overview of the EV markets listed on the US stock exchanges

Here's an overview of all prominent EV companies listed on US stock exchanges:

– NWTN – ICONIQ Holding Limited is developing an intelligent passenger vehicle (SPV) that focuses on artificial intelligence technologies, autonomous driving, Internet connectivity, and personalized passenger experiences;

– MULN – Mullen Automotive Inc. manufactures and sells electric vehicles. The company also operates CarHub, a digital platform that uses AI to offer an interactive solution for buying, selling and owning a car. MULN also provides battery technology and emergency care solutions;

– FFIE – Faraday Future Intelligent Electric Inc. engages in the design, development, manufacture, sale, and distribution of electric vehicles and related products in the United States and internationally;

– AYRO – Ayro Inc. designs and manufactures purpose-built four-wheel electric vehicles for universities, business and medical campuses, last mile delivery services and food service providers;

– VLCN – Volcon Inc. develops, manufactures and markets off-road electric vehicles in the United States and Latin America;

– GTEC – Greenland Technologies Holding Corporation designs, manufactures and markets transmissions for material handling vehicles in the People's Republic of China;

– ZEV – Lightning eMotors Inc. develops, manufactures, and markets zero-emission commercial vehicles and powertrains to commercial fleets, large enterprises, original equipment manufacturers, and US governments;

– SOLO – Electromeccanica Vehicles Corp. designs, manufactures and markets electric vehicles in Canada;

– XOS – Xos Inc. manufactures and sells commercial vehicles with batteries;

– ARVL – Arrival is engaged in research, development and design of commercial electric vehicles (EV), electric vehicle components, robotic manufacturing processes for electric vehicles and related software in the UK, USA, Russia;

– CENN – Centro Electric Group Limited designs and manufactures electric light and medium commercial vehicles in Europe, North America and Asia;

– FUV – Arcimoto Inc. designs, develops, manufactures, markets and leases three-wheeled electric vehicles in the United States;

– KNDI – Kandi Technologies Group Inc. designs, develops, manufactures and markets electric vehicle (EV) products and parts, as well as SUVs in the People's Republic of China and abroad;

– RIDE – Lordstown Motors Corp. designs, manufactures and markets the Endurance, an electric full-size pickup truck for fleet customers;

– WKHS – Workhorse Group Inc. designs, manufactures and sells zero-emission com-mercial vehicles in the United States;

– BLBD – Blue Bird Corporation designs, manufactures and markets school buses and related parts in the US, Canada and internationally;

– LEV – Lion Electric designs, develops, manufactures and sells all-electric medium and heavy-duty urban vehicles in North America;

– GOEV – Canoo Inc. designs, develops and manufactures electric vehicles for commercial and consumer markets in the United States;

– EVTV – Envirotech Vehicles Inc. supplies zero-emission electric vehicles in the US;

– PTRA – Proterra Inc. supplies commercial vehicles to the USA, European Union, Canada, Australia and Japan;

– NKLA – Nikola is a technology innovator and integrator working to develop energy and transportation solutions;

– FSR – Fisker Inc. develops, manufactures, sells, and gives for rent electric vehicles;

– XPEV – XPeng Inc. designs, develops, manufactures and sells smart electric vehicles in the People's Republic of China;

– LCID – Lucid Group Inc., designs and manufactures electric vehicles, electric vehicle powertrains and battery systems;

– PSNY – Polestar Automotive Holding UK PLC manufactures and markets premium electric vehicles;

– RIVN – Rivian Automotive Inc. designs, develops, manufactures and markets electric vehicles and accessories;

– NIO – NIO Inc. designs, develops, manufactures and sells smart electric vehicles in the People's Republic of China;

– LI – Li Auto Inc. designs, develops, manufactures and markets new energy vehicles in the People's Republic of China;

– F – Ford Motor Company designs, manufactures, markets and services a range of Ford trucks, passenger cars, SUVs, electric vehicles and Ford luxury vehicles worldwide;

– GP – Green Power Motor Company Inc. designs, manufactures and markets electric vehicles for the US and Canadian commercial markets;

– TSLA – Tesla Inc. designs, develops, manufactures, leases and sells electric vehicles and energy generation and storage systems in the United States, the People's Republic of China and abroad;

– GM – General Motors designs, manufactures and markets trucks, SUVs, passenger cars, and automotive parts and accessories in North America, Asia Pacific, the Middle East, Africa, South America, the United States and the People's Republic of China.

5. Results of research on the development of neuro-fuzzy models for predicting stock prices of EV companies

5. 1. Technical analysis of EV sector indicators

Closing price data for the EV sector companies described above was obtained from finance.yahoo.com for the period from 2022-01-03 to 2022-12-30, that is, for the entire 2022 calendar year. A total of 6430 data lines were collected, with each line representing 1 trading day. After calculating the indicators, it is noticed a clear correlation between indicators and stock price changes. Analysis of the relationship between price changes and indicators is described in Tables 1, 2. The first table is an example of Tesla. The second table shows a strong correlation between the first indicator of the future closing price with four indicators. One can immediately notice that the strongest correlation occurs between RSI and SO. But we are not interested in this relationship. It is noticeable in the table that the rest of the indicators correlate well only with the closing price of the next day. This gives reason to believe that our hypothesis that the future price can be predicted based on technical analysis indicators using neural networks is correct. Table 3 shows the correlation data for all companies in the EV sector.

The average correlation with the dynamic SMA50 is –0.62541, which is a good indicator of the relationship since the maximum negative value is –0.89731 and the minimum negative value is –0.30079. It was discovered that if the dynamic SMA50 shows an increase relative to the current closing price, then it can be predicted that the price will decrease, and vice versa, if the SMA50 approaches a negative value, then the forecast price is likely to be higher than the previous one. The average correlation with Signal MACD is 0.370600963 while the maximum value is 0.762446069 and the minimum value is –0.29263538. The average correlation with RSI is 0.435507 while the maximum value is 0.635983 and the minimum value is 0.009857. The average correlation with SO is 0.413566 while the maximum value is 0.620519 and the minimum value is –0.00436. In general, the closeness of the average correlation values to the maximum values suggests that, in general, all companies in the EV sector repeat the correlation one after another without any particular anomalies.

Table 1

An example of the analyzed data on the example of Tesla

Next day's closing price (forecast price)	Dynamic SMA50	Signal MACD	RSI	SO
280.0767	12.86434	–11.6706	54.90552	46.27659
290.5333	7.979157	–11.3368	55.09292	50.50576
301.7967	3.958761	–10.673	57.53411	67.63516
307.0533	–0.16792	–9.63306	54.56515	82.54161
331.3267	–2.23736	–8.30611	57.23238	91.0369
333.0367	–10.4003	–6.46262	62.6792	95.05478
337.9733	–11.1157	–4.35	69.28144	90.7248
336.88	–12.8896	–2.09076	70.50555	91.45913
363.9467	–12.7644	0.129263	75.89865	88.47398
366.5233	–21.6608	2.639867	79.12021	92.75514
364.6633	–22.3859	5.236085	77.82404	94.47866
359.2	–21.593	7.708256	80.63844	96.06776

Table 2

An example of correlation indicators of Tesla indicators

Indicators	Next close	Dynamic SMA50	Signal MACD	RSI	SO
Next close	1	–0.84503	0.738013791	0.623531	0.511985
Dynamic SMA50	–0.8450306	1	–0.87617359	–0.79052	–0.68405
Signal MACD	0.7380138	–0.87617	1	0.511572	0.352631
RSI	0.6235313	–0.79052	0.511572061	1	0.882882
SO	0.5119849	–0.68405	0.352630903	0.882882	1

Table 3

Correlation of EV sector indicators

Ticker (Next close)	Dynamic SMA50	Signal MACD	RSI	SO
NWTN	–0.89731	0.596634163	0.400544	0.276429
MULN	–0.73326	0.218656842	0.417135	0.461404
FFIE	–0.75631	0.400015456	0.39855	0.541143
AYRO	–0.62408	0.416035815	0.392304	0.359962
VLCN	–0.58622	0.30996797	0.445388	0.366992
GTEC	–0.56697	0.445687184	0.330855	0.241269
ZEV	–0.85313	0.478541505	0.497769	0.584182
SOLO	–0.61363	0.382813202	0.449764	0.492906
XOS	–0.86305	0.653251025	0.595027	0.5126
ARVL	–0.62779	–0.29263538	0.50677	0.492857
CENN	–0.89318	0.51195523	0.635983	0.529082
FUV	–0.86377	0.233041693	0.608226	0.620519
KNDI	–0.38812	0.540883435	0.452571	0.417749
RIDE	–0.67564	0.411817677	0.54562	0.485689
WKHS	–0.83502	0.717594239	0.593191	0.565645
BLBD	–0.31619	0.37175291	0.009857	–0.00436
LEV	–0.38175	0.070305396	0.25395	0.340309
GOEV	–0.53093	0.276729216	0.382871	0.427918
EVTV	–0.80584	0.694425515	0.584219	0.469241
PTRA	–0.53334	0.256241623	0.519854	0.470362
NKLA	–0.74248	0.542848886	0.443873	0.448419
FSR	–0.44685	0.19589531	0.355693	0.35707
XPEV	–0.45841	0.286159385	0.289439	0.356466
LCID	–0.58043	–0.016982798	0.591961	0.510966
PSNY	–0.47837	0.462375943	0.255794	0.213902
RIVN	–0.30079	–0.161422713	0.428548	0.398751
NIO	–0.67154	0.532200965	0.419411	0.402072
LI	–0.71655	0.762446069	0.330093	0.224725
F	–0.53723	0.378640875	0.40011	0.327516
GP	–0.51136	0.343830971	0.384696	0.416925
TSLA	–0.84503	0.738013791	0.623531	0.511985
GM	–0.37865	0.101509408	0.392616	0.413428

5. 2. Graphical representation of data

Dynamic SMA50, Signal MACD, RSI, SO were used as predictors for neural network training. As a response, the dynamics of NextClose change was used, which is described as a percentage. The construction of the developed fuzzy neural networks (FNN) is carried out on the basis of the ANFIS, by using the specialized Neuro-Fuzzy Designer package of the MATLAB software tool. This software has an easy-to-use graphical user interface [43]. ANFIS is a neural network with multiple inputs and one output, which in turn are fuzzy linguistic variables. In this case, the terms of input and output linguistic variables are described by membership functions. But before describing the neural network, let's describe the visualization of the collected data. Using the plot, semilogx, semilogy, loglog, area, stackedplot functions, plots of the data were plotted, which are displayed in Fig. 1. These plots give graphic confirmation (as well as the statistical data processing in the form of correlations described in section 3) that there are hidden dependencies in the data that we are looking for. Fig. 2 shows a sub-axis matrix containing column scatter plots. The matrix is created by the plotmatrix function. Fig. 3 shows plots of normal probability and quantile-quantiles of sample data.

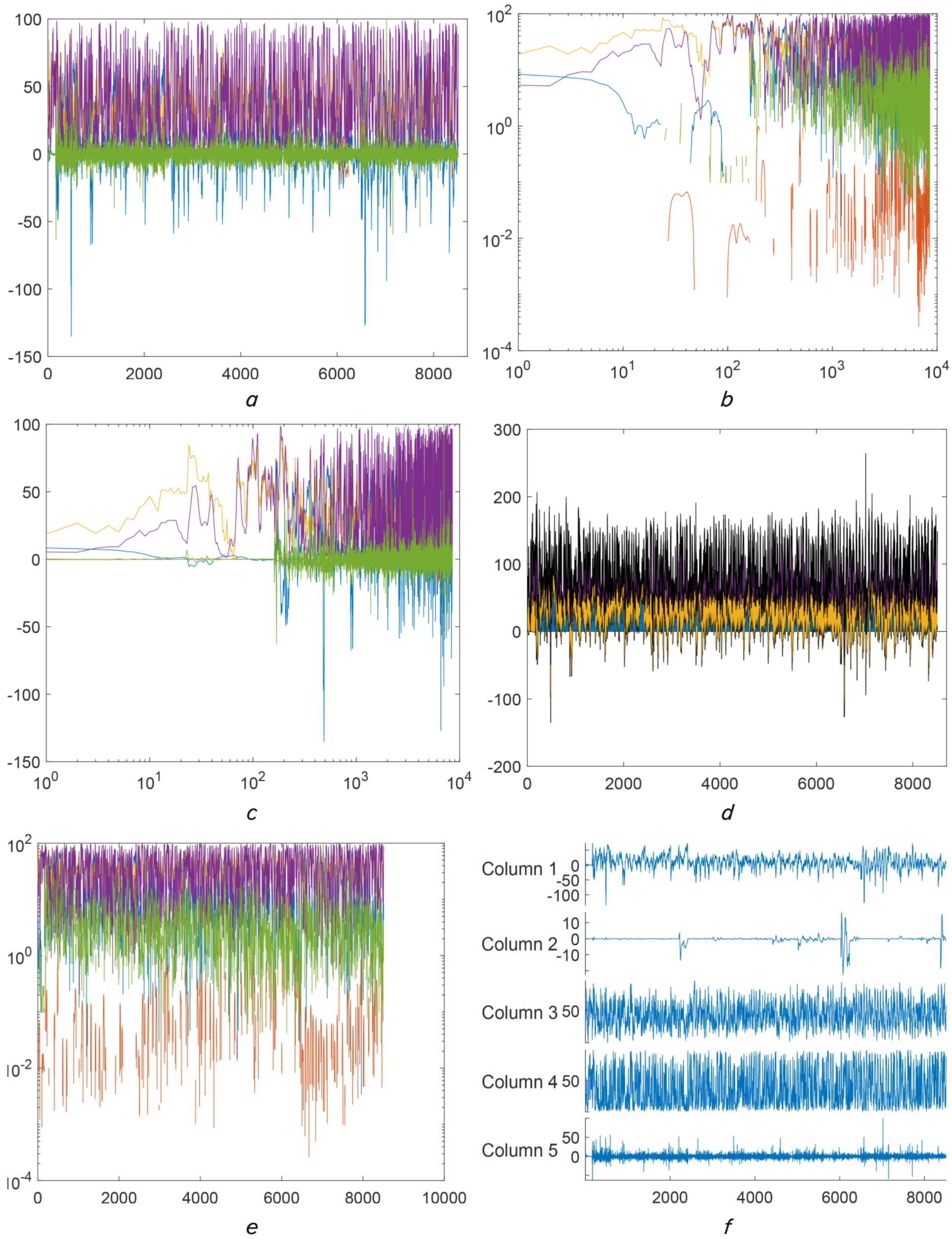

Fig. 1. Graphical representation of data processed by functions:
a – plot; *b* – loglog; *c* – semilogx; *d* – area; *e* – semiology; *f* – stackedplot

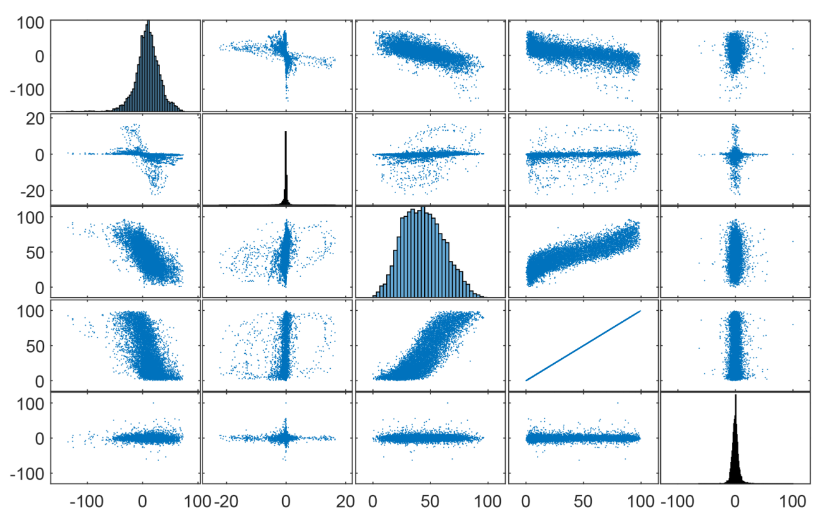

Fig. 2. Graphical representation of the sub-axis matrix containing the column scatter plots

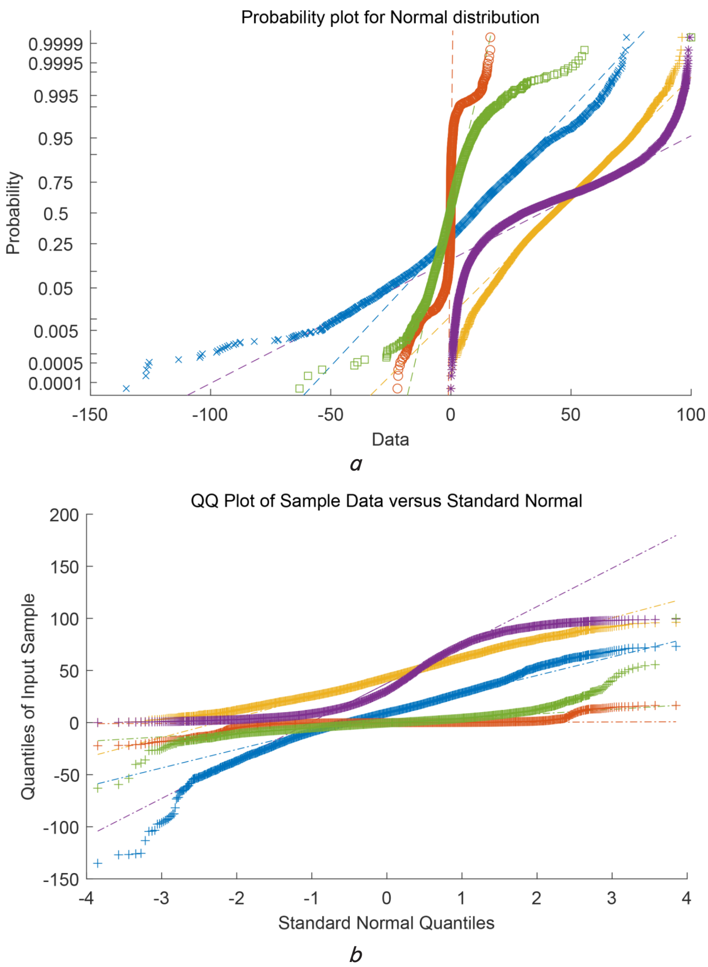

Fig. 3. Graphical representation of the functions: *a* – normplot; *b* – qqplot

Plots are created by normplot and qqplot functions. From the graphs, it can be seen that the data as a whole have a normal distribution, since the bulk of the data is along the baseline, although curvature is observed at the ends of the graphs.

5. 3. Fuzzy expert system architecture

Our work is to turn fuzzy outputs into clear buy, sell or hold trade recommendations that can be used by traders in the stock market. Fig. 4 shows the architecture of this solution. There are three modules on the system architecture: technical analysis module, convergence module and fuzzy inference module. The technical analysis module takes historical stock prices and calculates four technical indicators for each series. The convergence module converts technical indicators into new auxiliary variables to be used as input to a fuzzy inference system. The output of this convergence module serves as an input variable for the fuzzy inference system, and the fuzzy inference system (FIS) module generates a trading signal based on the rules defined in the rule base. An example of input data for the FIS is presented in columns 3–6 of Table 4. Fuzzy inference system designed as follows linguistic variables.

Input Variables:

– Dynamic SMA50: Represents the Simple Moving Average over 50 periods.

– Dynamic MACD: Represents the Moving Average Convergence Divergence.

– Dynamic RSI: Represents the Relative Strength Index.

– Dynamic SO: Represents the Stochastic Oscillator.

For each input variable, appropriate linguistic variables (fuzzy sets) are defined:

– Dynamic SMA50: Low, Medium, High.

– Dynamic MACD: Negative, Neutral, Positive.

– Dynamic RSI: Oversold, Neutral, Overbought.

– Dynamic SO: Oversold, Neutral, Overbought.

Output Variable:

– Next day's closing price: Represents the predicted change in price.

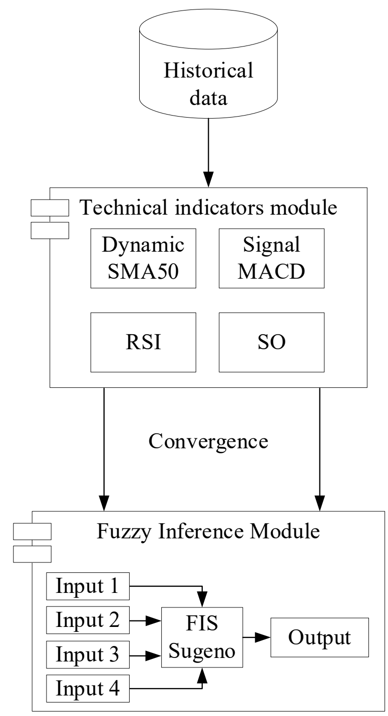

Fig. 4. Architecture of the fuzzy expert system

The FNN was trained on the basis of a training sample that contained 6430 sets representing a vector of technical analysis indicator values (input LV) and stock price growth dynamics values (output LV). The Neuro-Fuzzy Designer package allows to perform backpropagation training, the main purpose of which is to tune all layers of a multilayer structure by changing the weights of intermediate layers, and a hybrid method, which is a combination of least squares and backpropagation methods. The results of applying the FNN training methods are shown in Fig. 5–7.

Gaussian Function was used as activation function. Once defined the linguistic variables and fuzzy sets, it is possible to establish the linguistic rules that govern the relationships between the input and output variables. These rules are based on expert knowledge or data patterns. Each rule consists of an antecedent (the conditions) and a consequent (the action or conclusion).

For example:

– Rule 1: If «Dynamic SMA50» is «Low» and «Dynamic MACD» is «Negative» and «Dynamic RSI» is «Oversold» and «Dynamic SO» is «Neutral», then «Next day's closing price» is «Decrease»;

– Rule 2: If «Dynamic SMA50» is «Medium» and «Dynamic MACD» is «Neutral» and «Dynamic RSI» is «Overbought» and «Dynamic SO» is «Neutral», then «Next day's closing price» is «No Change»;

– ...

A set of such rules that cover different combinations of the input variables is defined.

ANFIS is built from 193 nodes, 81 linear parameters, which corresponds to the number of fuzzy inference rules (81 rules), 36 non-linear parameters. For training, 2000 epochs were set, and as a result, the minimum RMSE=5.90926 was obtained.

An example of output data for ANFIS is presented in 8 column of Table 4. This value of the FNN performance error satisfies our expectations. Fig. 8 shows the surfaces of the trained fuzzy model, which shows how the output LV depends on two input LVs, while the value of the third variable is fixed.

Fig. 5. Data for training FNN

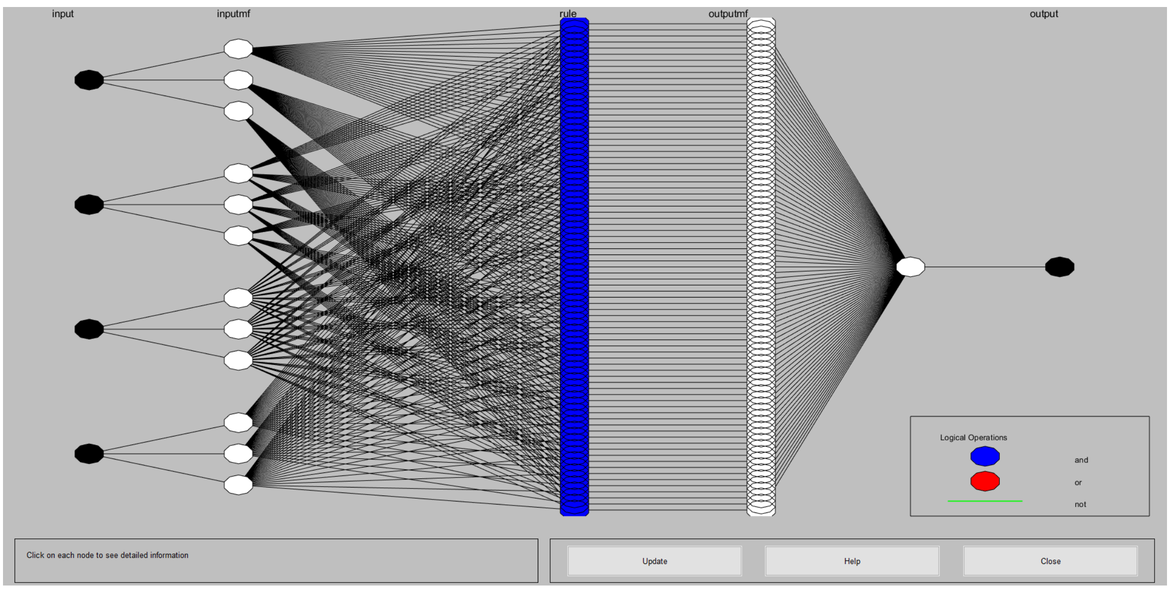

Fig. 6. The structure of the FNN

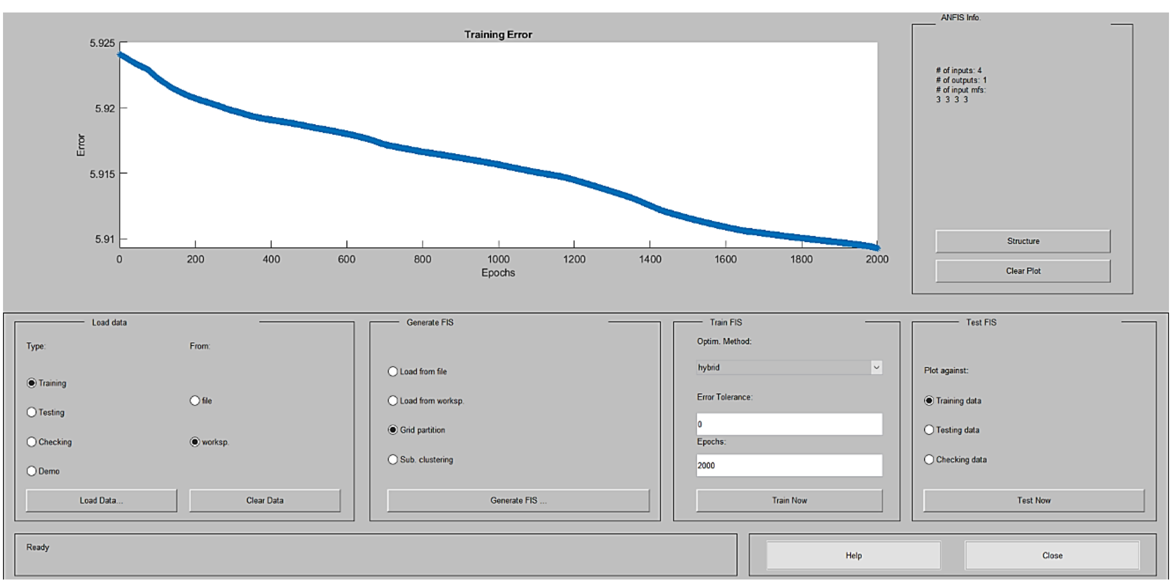

Fig. 7. The result of training FNN

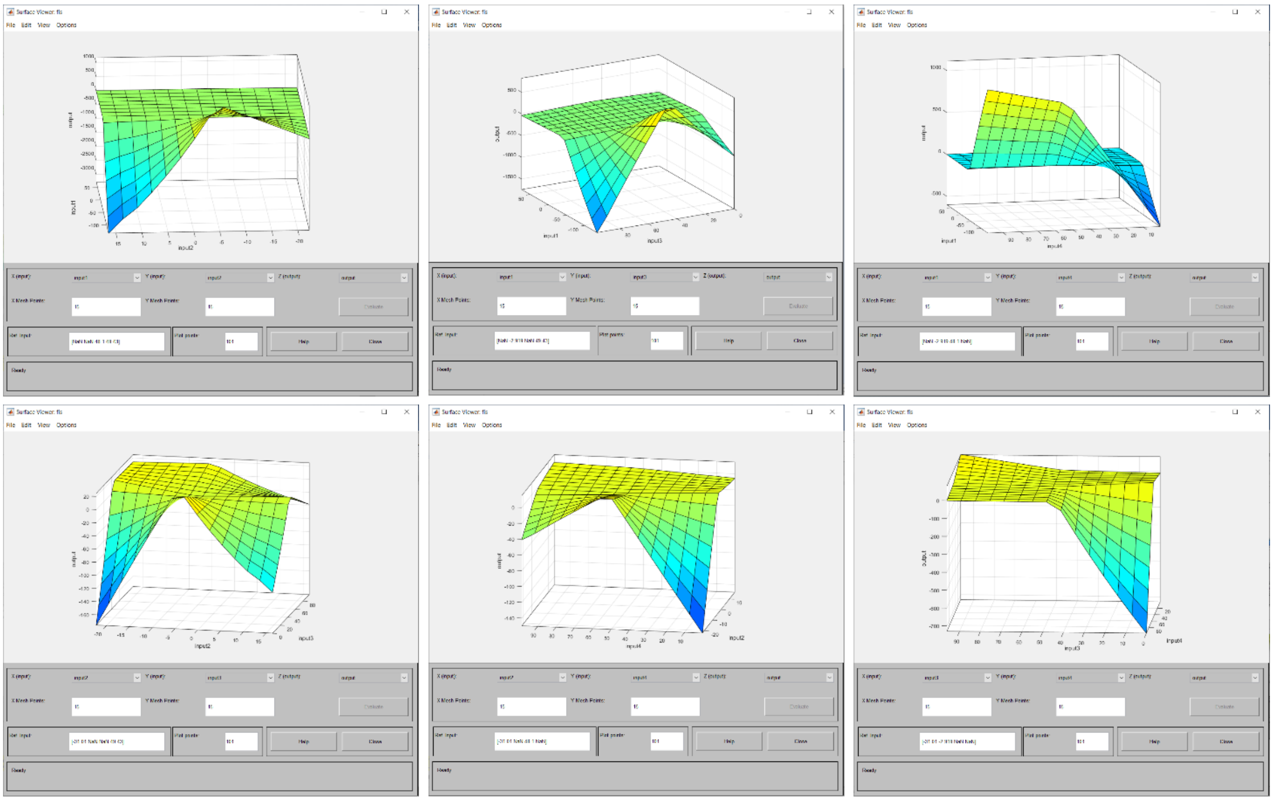

Fig. 8. Surfaces of the trained fuzzy model

A fuzzy inference system has been generated that contains 81 fuzzy production rules. A smooth and monotonous dependency graph of the reduced «inference surface» indicates a good «quality» of the inference mechanism and the sufficiency and consistency of the inference rules used, which proves that the forecasting mechanism based on the FNN has ample opportunities.

5. 4. Comparison with other well-known machine learning models

To test the ANFIS model, let's load the data on which the system was trained, a total of 6430 rows. Summing up those lines that gave a forecast of more than 1, it is possible to make a profit of 382.0470186 % out of 138 trades. Next, let's collect data from January 3 to January 17, 2023, for a total of 9 trading days. A total of 288 data rows were collected, with each row representing 1 trading day from 32 EV companies. Based on these data, let's calculate 4 input indicators, which were loaded into the FIS model. Let's sort the data, leaving the values where the forecast exceeded 1. In total, 20 trades out of a possible 288 are received. These data are presented in Table 4. In Table 4, let's add 2 columns Forecast and Profit in next 5 days in percent, as well as a date column, in contrast from 3 tables. For 20 trading operations, let's sum up the data of the Next day profit in % column and got 81.72898441 %. Summing up the Profit in next 5 days in % column, let's get 662.4214237 %.

The first investment algorithm: calculation of indicators before the close of the trading day, buying if the model shows more than 1, selling at the end of the next trading day. If to invest 1,000 USD in each operation from Table 4, then it is possible to make a profit of 817.2898441 USD in 9 days (4 % of 20,000 USD invested).

The second investment algorithm: calculation of indicators before the close of the trading day, buying if the model shows more than 1, selling at the end of the fifth trading day. If to invest 1000 USD in each operation from Table 4, then it is possible to get a profit of 6624.214237 USD in 14 days (33 % of $20000 invested).

Table 4 shows that the proposed ANFIS model can predict good profit signals in a short time frame. It has been practically proven that this model is suitable not only for day trading, but also has a cumulative profit power for 5 days. The pattern provides a powerful signal for the future growth of the stock. It is proposed in further works to program in the Python programming language [44] the collection and calculation of indicators of technical analysis indicators, the process of production output of the FIS system [45, 46], as well as the integration of the received signals with the TWS Interactive Brokers API.

Table 5 exhibits a comparison of selected machine learning models on the basis of their performance metrics; RMSE, R-squared, MSE, and MAE on a validation dataset. The order of the models in the table is from highest to lowest R-squared value. The models include decision trees (fine and coarse), neural networks (three-layered, bi-layered, and narrow), bagged trees, boosted trees, support vector machines (SVMs) with different kernels (linear, quadratic, cubic, and Gaussian), Gaussian process regression (GPR) with different kernels (exponential, squared exponential, Matern 5/2, and rational quadratic), linear regression models (robust, interactions linear, stepwise linear, and plain linear), and two hybrid models (Bayesian regularization-backpropagation neural network and ANFIS). The limitations of the models can be inferred from their performance metrics. For example, models with higher RMSE, MSE, and MAE values indicate higher prediction errors, while lower R-squared values suggest a weaker fit to the data. It's important to consider the specific requirements and constraints of the problem domain when selecting a model, as each model may have its own limitations in terms of interpretability, complexity, or sensitivity to outliers. When it comes to forecasting price areas, there are several limitations that need to be considered. The accuracy and reliability of price area forecasting heavily rely on the quality and availability of historical data. If the available data is limited, incomplete, or contains errors, it can adversely affect the forecasting accuracy. Price areas in financial markets are influenced by various factors, including economic conditions, political events, market sentiment, and external shocks. Sudden and unpredictable changes in market volatility can make it challenging to accurately forecast price areas.

Table 4

The results of the experiment

Ticker (Next close)	Date	Dynamic SMA50	Signal MACD	RSI	SO	Next day profit in %	Forecast	Profit in next 5 days in %
ARVL	2023-01-06	45.37609	–0.06351	38.83929	65.45001	6	13.8722	149.4447
TSLA	2023-01-03	39.20518	–17.6685	16.68154	14.93755	5.124885	11.7333	9.852848
TSLA	2023-01-05	36.50483	–18.3488	23.43321	10.27481	2.46511	10.4928	11.58471
TSLA	2023-01-04	35.3566	–18.0606	23.20761	14.10685	–2.90391	10.0765	8.404869
TSLA	2023-01-06	34.1103	–18.4717	25.0196	14.97339	5.934901	9.888	8.180784
TSLA	2023-01-09	29.33607	–18.3354	32.80262	20.91097	–0.76814	6.5285	9.672356
TSLA	2023-01-10	28.98865	–18.0166	32.5965	29.71236	3.676906	6.0373	10.44049
ARVL	2023-01-05	43.45804	–0.06736	39.72603	56.09795	–6.54206	4.8232	125.31
FUV	2023-01-06	56.00793	–1.71669	43.3372	75.23318	5.154639	4.0276	36.25994
FUV	2023-01-03	59.54228	–2.01295	45.11785	32.76881	25.73964	3.2426	11.38832
FUV	2023-01-09	52.36888	–1.62061	43.40278	61.55251	1.40056	3.0327	62.43577
FUV	2023-01-10	50.3368	–1.52634	47.06601	53.88128	22.37569	2.5255	61.03521
TSLA	2023-01-11	25.43942	–17.4894	41.04643	41.46617	0.275927	1.9262	9.336027
CENN	2023-01-03	42.41737	–0.10681	48.32354	53.58621	5.247225	1.5308	12.30165
CENN	2023-01-05	39.00076	–0.09424	54.25321	50.54023	0.418616	1.4467	28.07077
CENN	2023-01-06	37.63591	–0.08821	54.90731	51.85057	6.817067	1.43	27.97164
CENN	2023-01-04	38.33383	–0.10045	53.30021	54.43678	–2.66059	1.3316	16.30622
ARVL	2023-01-04	40.16918	–0.07116	46.72897	38.99293	–7.75862	1.2026	17.55142
CENN	2023-01-09	32.19326	–0.08197	56.69401	53.96552	2.479339	1.1251	24.6765
CENN	2023-01-10	29.37111	–0.07557	63.20151	58.5977	9.251792	1.0111	22.19716

Table 5

Comparison of machine learning models

Models	RMSE	R-Squared	MSE	MAE
Linear (LR)	6.9594	0.83	42.515	4.0855
Interactions Linear (ILR)	8.9635	0.83	69.564	4.0858
Robust Linear (RLR)	10.972	0.77	100.665	4.0828
Stepwise Linear (SLR)	7.9602	0.82	47.524	4.0866
Fine Tree	13.487	0.53	147.202	7.8798
Coarse Tree	12.547	0.57	138.876	6.3887
Linear SVM (LSVM)	9.9702	0.8	87.643	4.0807
Quadratic SVM (QSVM)	10.9754	0.73	102.705	4.0817
Cubic SVM (CSVM)	10.994	0.71	104.928	4.093
Coarse Gaussian SVM (CGSVM)	10.9711	0.78	94.654	4.0782
Boosted Trees (BoostT)	11.003	0.7	119.036	6.1065
Bagged Trees (BagT)	11.1182	0.68	120.432	6.2128
Squared Exponential GPR (SE-GPR)	10.9731	0.76	101.677	4.0904
Matern 5/2 GPR (M52-GPR)	9.969	0.81	84.629	4.0792
Exponential GPR (Exp-GPR)	10.9732	0.75	102.679	4.088
Rational Quadratic GPR (RQ-GPR)	9.9682	0.84	85.619	4.0863
Narrow Neural Network (NNN)	10.9987	0.71	105.984	5.1286
Bilayered Neural Network (BLNN)	11.1321	0.67	122.602	6.2099
Trilayered Neural Network (TLNN)	11.1561	0.63	122.897	6.2463
Bayesian regularization-backpropagation neural network (BR-BPNN)	5.9094	0.927	34.566	3.97143
Adaptive Neuro-Fuzzy Inference System (ANFIS)	5.90926	0.974	32.457	2.6877

Examining Table 5, it is possible to observe that ANFIS model has a R-squared value of 0.974 which is quite remarkable and implies that it fits the data well. The BR-BPNN model outperforms all other models in R-squared, with a value of 0.927 which is a highly satisfactory fit. Upon analyzing Fig. 9, the evaluation metrics chart, it is evident that the ANFIS model has the lowest RMSE, MSE, and MAE values. This suggests that it provides the greatest accuracy in terms of prediction errors compared to other models. Furthermore, BR-BPNN model also performed relatively well with these metrics.

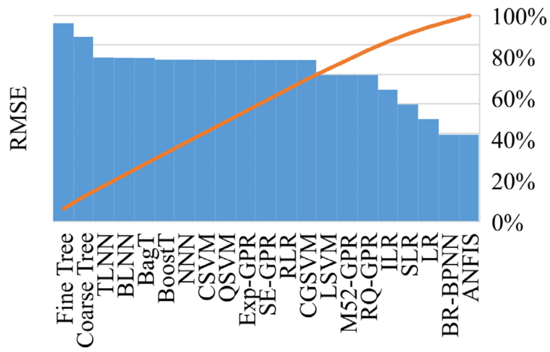

Fig. 9. Pareto chart of evaluation metrics

Linear models (e.g. robust, interactions linear, stepwise linear and plain linear) are generally less effective than other models and the decision tree models (fine and coarse) have relatively poor performance metrics (e.g. higher RMSE, MSE and MAE values). All in all, the ANFIS and BR-BPNN models are the most proficient when it comes to this particular dataset. The M52-GPR, RQ-GPR, and several SVM kernels also show remarkable results. It seems that linear models and decision tree models aren't very helpful in this particular scenario. Additionally, neural network models (three-layered, bi-layered, and narrow) and ensemble models (bagged trees and boosted trees) provide satisfactory results with low RMSE, MSE and MAE values. It's fascinating to witness the excellent performance of kernel-based models such as GPR and SVM despite executing on different mathematical techniques and presumptions. It's conceivable that the distinct kernels could capture different sort of connections between the input features and the target variable, resulting in amplified performance.

6. Discussion of the results of a study on stock price forecasting using a neuro-fuzzy model

By applying statistical processing methods to technical analysis data, we were able to identify relevant patterns and relationships between these indicators. This move allowed to gain insight into share price performance in the EV sector and laid the foundation for our predictive modeling efforts. The results displayed in Tables 1–3 showed the influence of the indicators, which helped to draw up fuzzy inference rules. A correlation table of indicators of technical analysis indicators with the dynamics of price changes was formed. The study of the entire EV sector showed that the average correlation with the dynamic SMA50 is –0.62541, this is a good indicator of the relationship since the maximum negative value is –0.89731, and the minimum negative value is –0.30079. It was discovered that if the dynamic SMA50 shows an increase relative to the current closing price, then it can be predicted that the price will decrease, and vice versa, if the SMA50 approaches a negative value, then the forecast price is likely to be higher than the previous one. The average correlation with Signal MACD is 0.370600963 while the maximum value is 0.762446069 and the minimum value is –0.29263538. The average correlation with RSI is 0.435507 while the maximum value is 0.635983 and the minimum value is 0.009857. The average correlation with SO is 0.413566 while the maximum value is 0.620519 and the minimum value is –0.00436. In general, the closeness of the average correlation values to the maximum values suggests that, in general, all companies in the EV sector repeat the correlation one after another without any particular anomalies.

To facilitate a better understanding of the complex datasets, let's utilize graphical representations through different plot functions. Instead of presenting raw numerical values or textual descriptions, these visualizations enhanced the interpretability of the data. Various types of plots, such as line plots, scatter plots, and bar charts, were employed to illustrate different aspects of the dataset, including trends, correlations, and distribution characteristics. The results displayed in Fig. 1–3 proved the correlations derived from the statistical processing of the data. The charts gave graphical confirmation that there were hidden dependencies in the data that we were looking for. From the graphs, it can be seen that the data as a whole have a normal distribution, since the bulk of the data is along the baseline, although curvature is observed at the ends of the graphs.

In order to assess the performance of our neuro-fuzzy model, a comparative analysis with other well-known machine learning models was conducted. By employing appropriate evaluation metrics such as mean squared error, accuracy, and precision, the predictive capabilities of different models were compared. Table 5 and Fig. 9 prove the effectiveness of our proposed approach in predicting the stock prices of companies in the electric vehicle sector. Linear models (such as robust, interaction, stepwise and plain linear) usually don't perform as well compared to other models. Decision tree models (including both fine and coarse types) tend to have poorer performance metrics such as higher RMSE, MSE and MAE values. After analyzing the data, ANFIS and BR-BPNN models were found to be the best performers. M52-GPR, RQ-GPR and few SVM kernels also delivered significant results. Linear models and decision tree models however didn't present much value in this case. Furthermore, employing different types of neural networks (trilayered, bilayered, and narrow) as well as ensemble models such as bagged trees and boosted trees can produce results with low RMSE, MSE and MAE values. It is truly remarkable to see the high level of performance that GPR and SVM models display, even though they are based on different mathematical techniques and assumptions. It's likely that distinctive kernels could detect various types of correlations between the input features and the target variable, thus leading to improved performance. For ANFIS training, 2000 epochs were allocated resulting in a minimum RMSE=5.90926.

Furthermore, predictive experiments to validate the performance of our model were carried out. By feeding the trained model with unseen data, its ability to generalize and make accurate predictions on new instances was accessed. The experimental results in Table 4 were analyzed in terms of prediction accuracy, robustness, and stability, providing insights into the practical viability of the neuro-fuzzy forecasting model. The conducted experiments proved the performance of the predictive model. For 20 trading operations, the Next day profit in % amount was 81.72898441 %, and the Profit in next 5 days in % amount was 662.4214237 %. Table 4 shows that the proposed ANFIS model can predict good profit signals in a short time frame. It has been practically proven that this model is suitable not only for day trading, but also has a cumulative profit power for 5 days. The pattern provides a powerful signal for the future growth of the stock. ANFIS is able to handle uncertainty and imprecision in the data, which is common in stock market data. This allows it to make more accurate predictions about future stock prices. ANFIS can handle both linear and non-linear relationships in the data. This is particularly useful in stock price forecasting, where the relationships between different variables are often complex and non-linear. ANFIS can be updated and retrained as new data becomes available, which allows it to adapt to changing market conditions. This makes it more robust and able to make accurate predictions in different market scenarios. ANFIS can handle multiple inputs, such as technical indicators, news data, and other relevant information, which makes it more comprehensive than other methods. ANFIS can handle missing data, which is a common problem in stock market data.

The combination of fuzzy logic and neural networks gives the advantage of this study compared to those known in this field. The neuro-fuzzy model was aimed at capturing the non-linear relationships and uncertainties present in stock price dynamics. The training process included iterative optimization methods to fine-tune the model parameters and improve its predictive performance.

7. Conclusions

1. Through statistical processing of technical analysis data, we successfully established correlations among the indicators within the EV sector. This step provided valuable insights into the interdependencies and trends present in the stock prices of EV companies. Average correlations: Dynamic SMA50=–0.62541; Signal MACD=0.370600963; RSI=0.435507; SO=0.413566.

2. By visualizing the data using graphical representations, we enhanced the understandability of the complex datasets, enabling to discern meaningful patterns and characteristics.

3. The construction of a neuro-fuzzy forecasting model based on a fuzzy expert system architecture was a crucial step in our research. This model incorporated the numerical parameters derived from the technical analysis indicators as inputs. By integrating fuzzy logic and neural networks, we aimed to capture the non-linear dynamics and uncertainties associated with stock price movements. The training process of the model involved iterative optimization, leading to improved predictive performance. The system architecture comprises three distinct modules, namely the technical analysis module, the convergence module, and the fuzzy inference module. The technical analysis module performs computations on historical stock prices, generating four technical indicators for each series. The convergence module transforms these technical indicators into fresh auxiliary variables, which are subsequently utilized as input for a fuzzy inference system. The output produced by the convergence module serves as an input variable for the fuzzy inference system module, where a trading signal is generated based on predefined rules within the rule base.

4. To evaluate the performance of our proposed model, we conducted a comprehensive comparison with other well-known machine learning models. This comparative analysis enabled to gauge the effectiveness and superiority of our neuro-fuzzy model in predicting the stock prices of EV companies. By employing appropriate evaluation metrics, we quantitatively assessed the accuracy and precision of the model, establishing its potential in the domain of stock price prediction. ANFIS shows: RMSE=5.90926; R-Squared=0.974; MSE=32.457; MAE=2.6877.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

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