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CAPITAL MARKET BEHAVIOR AND STOCK FORECASTING – A NEURAL NETWORK APPROACH TO LUFTHANSA'S SHARES*

Jakub Horák

*Institute of Technology and Business, School of Expertness and Valuation, České Budějovice 37001, Czech Republic
Institute of Technology and Business, Department of Economics, Management and Marketing, Prešov 08001, Slovakia*

E-mails: horak@mail.vstecb.cz; horak@vste.sk

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Abstract. The study deals with the development and prediction of stock prices of a selected European airline, Deutsche Lufthansa Group, in the context of its presence on capital markets between 2004 and 2024. The main objective is to analyse the time series of historical daily stock prices of Deutsche Lufthansa Group and use this data to forecast price development in the near future using the method of artificial neural networks in the Statistica 14 software. The study further identifies the key external and internal factors influencing the volatility of the company's stock, as financial crisis, political unrest, escalation of the European debt crisis, government strikes, acquired parts of other companies, increasing competition from low-cost carriers, growing pressure to reduce CO2 emissions etc. The results show that predictive models based on multiplayer perceptron networks can effectively predict short term development of stock prices in the dynamic environment of capital markets. The results revealed that the prediction for Lufthansa's share prices show a slightly upward and stable trend. This trend reflects the positive expectation and stabilization of costs, which may indicate renewed investor confidence in the company's long-term recovery. The findings offer a valuable insight for investors, analysts, and the academic community and can serve as a foundation for further research on stock price prediction in the aviation industry.

Keywords: stocks; capital market; historical prices; airline industry; artificial neural networks; Artificial Intelligence (AI), investment

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1. Introduction

The aviation industry has long been one of the key sectors of the global economy. Its importance goes far beyond tourism – it supports international trade, labor mobility and employment. At the same time, it is a sector that is extremely sensitive to changes in external conditions and must adapt quickly to new trends. In recent decades, the industry has undergone fundamental changes, largely caused by globalization. Consumer preferences are constantly evolving, which forces airlines to innovate services and improve their quality (Adeniran et al., 2023). Air transport is one of the most regulated industries (Gabor et al., 2022) and, despite a temporary slowdown during the COVID-19 pandemic, remains highly competitive. A number of factors influence airlines' pricing and competitive strategies. For example, Ryanair uses competitive advantages in the labor market and legal frameworks (Harvey & Turnbull, 2020). Another strategy is to increase flight frequencies, which can discourage new low-cost carriers without reducing demand (Valido et al., 2020). In an environment with limited airport capacity, it is relatively easy to prevent the entry of competitors, while in higher capacity, access to new carriers

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must be allowed. The significant position of aviation is also conditioned by external influences, which include in particular oil prices, geopolitical events or the characteristics of tourist destinations (Domínguez et al., 2021). Efficient fuel use and fleet modernization also play an increasingly important role, which allow for reducing costs and emissions and increasing the quality of services provided (Oliveira et al., 2021; Oliveira et al., 2022). Accurate ticket pricing is key to ensuring profitability, yet revenue management systems often monitor individual variables separately, without their broader context (Jayram et al., 2023). In addition, ongoing liberalization, privatization, and changing government policies significantly influence airline strategies and the operation of regional airports (Pietreanu, 2019). These factors show that aviation remains one of the most dynamic and vulnerable sectors of the global economy. This dynamic development is inevitably reflected in the capital markets, which represent one of the most important sources of financing for airlines and a means of raising capital for fleet modernization, expansion, or overcoming crisis periods. Airline shares therefore serve not only as an investment tool, but also as a sensitive indicator of the overall health of the industry. Airline share prices are highly sensitive to volatile and cyclical factors, which makes their prediction particularly difficult (Zheng et al., 2021). Nevertheless, their analysis is essential for investors and analysts, as it allows them to better estimate risks and opportunities in an environment that is extremely dynamic and prone to unexpected shocks. For airlines themselves, the development of shares is an important indicator of investor confidence and a factor that affects their ability to raise funds for further growth. Forecasting airline shares therefore has a dual meaning - for markets and investors, it provides a tool for decision-making and portfolio diversification, and for airlines it is a source of strategic information that reflects not only their own economic results, but also the broader macroeconomic and geopolitical environment. Given that aviation is one of the most vulnerable and at the same time the most strategic sectors of the world economy, the issue of forecasting shares is becoming one of the key topics of current research and practice.

The aim of this study is to determine the development of Deutsche Lufthansa Group's stock prices, analyse the historical time series of daily stock prices, and predict future price trends. To achieve this goal, the following research questions were formulated:

- RQ1: What factors have had the greatest impact on the volatility of Deutsche Lufthansa Group's stock prices between 2004 and 2024?
- RQ2: How is Deutsche Lufthansa Group's stock price expected to evolve during January and February 2025?

2. Theoretical background

Predicting stock market developments has long been considered a very difficult task, mainly due to their inherent nonlinearity and complexity (Nabipour et al., 2020; Wang et al., 2024; Peternel & Bukvič, 2024). The main obstacle is the difficulty of reliably identifying simple patterns in an environment that is highly dynamic and dependent on a wide range of variables (Chi et al., 2022). Although traditional econometric approaches such as regression models, ARIMA or GARCH allow a certain degree of explanation of historical developments, they often encounter limits in capturing nonlinear relationships and complex market dynamics. This significantly limits their ability to generate accurate predictions, especially in an environment characterized by frequent fluctuations and the influence of external factors (Wang et al., 2023).

These limits are being addressed by the increasing use of artificial intelligence and machine learning methods, which have demonstrated high efficiency in analyzing large historical data sets (Vijh et al., 2020). These methods can reveal hidden patterns and relationships that traditional statistical tools often fail to capture. However, historical data alone is not enough to achieve fully reliable results, as financial markets are also shaped by factors that cannot be easily quantified and are difficult to capture even through neural networks (Barra et al., 2020; Katina et al., 2024). The prediction of stock prices is influenced by a wide range of factors - from volatility and recent returns to macroeconomic indicators to public sentiment (Ramezani et al., 2019; Nti, 2021). Moreover, the growing volume of data generated from different sources increases the complexity of their integration, as individual data streams often have different formats and structures (Khan et al., 2020). In addition to traditional financial and economic variables, less conventional sources of information are also gaining

importance. Social media and financial news can significantly change investor behavior in a short time, which emphasizes the need to include them in predictive algorithms.

Azzolina et al. (2021) state that the factors influencing the development of airline stock prices are extremely diverse. These include primarily fuel prices, which constitute a significant part of airlines' operating costs, as well as macroeconomic indicators such as GDP growth or inflation, as well as geopolitical events that can affect both air transport demand and operating costs. According to Drammeh (2024), the development of tourism and consumer preferences is also a specific factor, which can change rapidly under the influence of global crises, such as the COVID-19 pandemic. Environmental regulations and market liberalization are other important determinants that fundamentally affect the management of airlines and are reflected in the value of their shares (Penela et al., 2023).

Airline stock prediction is therefore considered one of the key challenges of current research. Its results are important not only for investors, who can use them to better manage risks and diversify portfolios, but also for airlines themselves. The development of stocks reflects not only their current financial results, but also investor confidence, which affects the ability of companies to raise capital for modernization and expansion (Thorbecke, 2020).

In recent years, there has been an increasing number of studies focusing on the application of artificial intelligence methods in stock prediction, both in stock markets in general and in the transport and aviation sectors specifically (Sonkavde et al., 2023). These works confirm that airline stock prediction is becoming an increasingly important topic of academic and practical interest. An example is the study by Xu et al. (2023), which focused on the prediction of daily closing prices of three major Chinese airlines. The authors used a combination of LASSO to select relevant predictors and external variables from the macroeconomic and aviation sectors. The results showed that this approach provides more stable and accurate forecasts than traditional models and emphasizes the importance of combining technical and fundamental indicators. Zheng et al. (2021) focused on the aerospace sector, including manufacturers and operators, and tested a hybrid model combining principal component analysis (PCA) with a recurrent neural network (RNN). Their results confirmed that appropriate data pre-treatment using PCA increases prediction accuracy and improves computational efficiency, while it was shown that specific company characteristics affect the optimal model settings. Another contribution to this area was made by Choi and Choi (2023), who focused on American Airlines shares. Their LSTM model was enriched with information from the oil market, since the price of fuel is one of the key cost factors for airlines. The study confirmed that including oil price determinants in the prediction significantly improves the accuracy of the results and better reflects the sensitivity of airline stocks to fuel-related costs. Deb (2021) focused on the public sentiment factor, examining the short-term volatility of the stocks of three US airlines - American Airlines, Delta Airlines and United Airlines. He included signals from Twitter and Google Trends in modified GARCH models, testing the effect of "internet attention" on stock performance. The findings showed that incorporating this data significantly improves the models' ability to predict short-term fluctuations and confirms that investor behavior is increasingly shaped by the online environment.

3. Research objective and methodology

Deutsche Lufthansa Group, also known as Lufthansa Airlines, headquartered in Cologne, was established in 1953. It is Germany's largest airline and one of the leading carriers in Europe. The main hubs are Frankfurt and Munich airports. Lufthansa AG is the core entity within the Deutsche Lufthansa Group (LHAG), which also encompasses SWISS, Austrian Airlines, Brussels Airlines, and Eurowings. LHAG provides air transport services to over 200 destinations worldwide and is a co-founder of the Star Alliance. The company is structured into two primary segments: "Passenger Airlines" and "Airline Services", the latter of which includes logistics and technological operations (Lufthansa Group, 2025).

3.1 Data

Historical stock price data used for the time series analysis and predicting stock price of Deutsche Lufthansa Group (LHAG) were obtained from the financial markets' platform Investing.com (Investing.com, 2025). The dataset covers the period from 2 January 2004 to 31 December 2024 and includes only trading days (i.e.,

excluding weekends and public holidays). Since LHAG shares are not traded individually, data relating to the entire group, available on the German stock exchange BATS Europe (now known as “Cboe Europe Equities”), will be used for the period from 25 November 2008 to 31 December 2024. The data will be downloaded in .csv format and subsequently processed in Microsoft Excel to prepare them for analysis.

The data will be divided into seven columns, specifically date, closing price, opening price, daily high, daily low, trading volume, and daily change. This procedure will be performed for the entire selected period and the related data will be modified to ensure the compatibility with the requirements of the subsequent analysis. For the characterization of Lufthansa and the relevant historical events, supplementary data from CAPA Centre for Aviation, the Statista platform, and the Lufthansa Group’s official website sources will be drawn. Furthermore, data from economic and statistical sources such as Google Finance, Sustainalytics, and the company’s annual report for the fiscal year 2023 will be used.

3.2 Methods

To answer RQ1, graphical analysis, document analysis, and time series analysis will be used based on a review of available sources. Historical events and related documents that have influenced the impact on the share price and its subsequent market development will be examined.

To answer RQ2, a time series analysis and prediction of the development of Deutsche Lufthansa Group’s share price will be carried out. For this purpose, a neural network model will be applied using Statistica (Data Science Workbench, version 14) by TIBCO Software Inc. First, it is necessary to preprocess the data into a format compatible with the neural network requirements. The analysis will use daily closing prices of Deutsche Lufthansa Group shares. After the import of data into the software, necessary values for descriptive statistics will be calculated, including mean, median, modus, standard deviation, variance, skew, kurtosis, as well as minimum and maximum values, etc.

The regression using neural network method will be applied. The output of its application is the creation of two neural network models, specifically a Radial Basis Function (RBF) and a Multilayer Perceptron (MLP) network. The dataset used for the neural network calculations will consist of 14,672 input values. The dependent variable will be the closing stock prices of individual airlines, while the independent variable will be time. Figures 1 and 2 provide a graphical representation of the RBF and MLP neural network models.

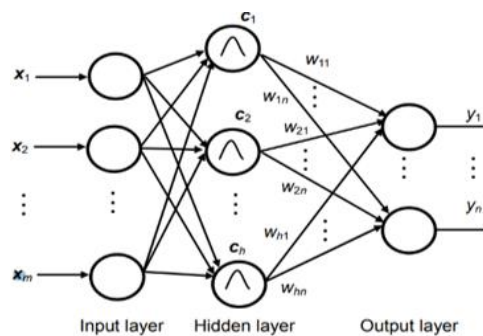


Figure 1. Radial Basis Function (RBF)

The Radial Basis Function (RBF) has the following mathematical expression:

$$y(\vec{x}) = e^{-\left(\frac{\|\vec{x} - \vec{c}\|}{b}\right)} \quad (1)$$

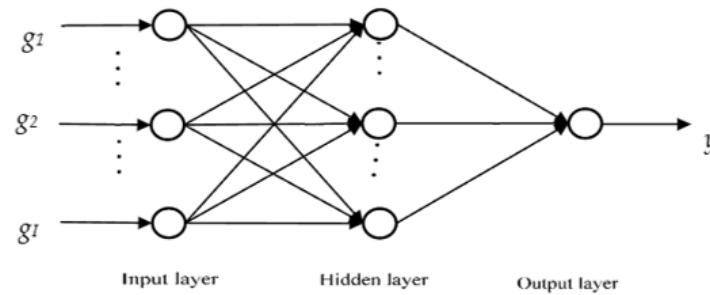


Figure 2. Multilayer Perceptron (MLP) network

The mathematical expression of the Multilayer Perceptron (MLP) networks is as follows:

$$y(\vec{x}) = \sigma(\sum_{i=0}^n w_i x_i) \quad (2)$$

Time series will then be randomly divided into three categories, specifically training, testing, and validation. The training category will serve as a foundation for creating the neural network structures and will thus contain 80% of the input data. The testing category is used to validate the resulting reliability of the trained neural network, while the validation category will monitor ongoing reliability and performance during the training process. These categories will thus contain 10% of the input data each. For each company, a total of 1,000 neural networks will be generated. From these, the 10 most successful neural networks with the best characteristics and suitable for predicting future company performance will be selected using an error function based on the least squares method. The mathematical expression of the least squares method is as follows:

$$E_{sos} = \frac{1}{2N} \sum_{i=1}^N (y_i - t_i)^2 \quad (3)$$

The hidden layers of the multilayer perceptron (MLP) neural network for Deutsche Lufthansa Group will contain at least 2 and a maximum of 25 neurons. Similarly, the hidden layers of the radial basis function (RBF) network will also contain between 2 and 25 neurons. The activation functions used in the training algorithm for both the hidden and output layers of the MLP network will include sine, exponential, hyperbolic tangent, logistic, and linear (also referred to as the identity or linear sigmoid function). All other software settings will remain default, with automatic network creation (ANS) enabled. Table 1 presents the mathematical formulas of the respective activation functions.

Table 1. Activation function and their mathematical representation

Function	Definition	Interval
Sine	$\sin(a)$	$[0; 1]$
Exponential	e^{-a}	$(0; +\infty)$
Hyperbolic tangent	$\frac{e^a - e^{-a}}{e^a + e^{-a}}$	$(-1; +1)$
Logistics	$\frac{1}{1 + e^{-a}}$	$(0 ; 1)$
Identical sigmoid	a	$(-\infty; +\infty)$

Source: Author according to Šuleř and Machová (2019)

The BFGS (Broyden–Fletcher–Goldfarb–Shanno) optimization algorithm will be used to adapt the machine learning model. The final step of the process will be validation, which involves measuring the difference

between the stock price predictions generated by the neural networks and the actual stock prices of each airline. The result of this validation will be the residuals, representing the discrepancies between predicted and observed values.

4. Results

This chapter presents the results and findings obtained through the application of the aforementioned methods, using tables and figures where appropriate. The first and second subchapters outline the general characteristics of the Deutsche Lufthansa Group, and the historical development of the closing stock prices for the period 2008–2024. The third subchapter provides descriptive statistics. The final section outlines the anticipated future development of the closing stock prices of the Deutsche Lufthansa Group.

4.1 General characteristics of the company

From an economic perspective, the Deutsche Lufthansa Group reported total assets of EUR 45.32 billion and total liabilities of EUR 35.61 billion at the end of the fiscal year 2023 (1 January 2023 to 31 December 2023). Net income amounted to EUR 1,7 billion, with a net profit margin of 7.6%. Earnings before interest, taxes, depreciation, and amortization (EBITDA) reached EUR 3.94 billion, operating cost totalled EUR 5.35 billion, and free cash flow (FCF) stood at EUR 1.846 billion. However, the return on assets (ROA) was only 2.93%, while the return on capital (ROC) reached 13.1%. At the end of the fiscal year 2023, a total of 1.20 billion shares were outstanding, and earnings per share (EPS) amounted to EUR 1-39. According to Google finance (2024) and Lufthansa Group (2025), the company operated a fleet of 321 aircraft by the end of 2024, primarily comprising models such as Airbus A319, A320, A321, A330, A340, A350, A380, A320NEO, A321NEO, as well as Boeing 747, 787, CRJ-900 Lufthansa Group (2025). Currently, the increasingly cited topic of sustainability and corporate responsibility is also being addressed in the aviation industry. In 2024, the Lufthansa Group received an ESG score of 26.0 (rated A–), indicating medium risk (Sustainalytics, 2024). During 2023, the Lufthansa Group operated 14% more flights compared to 2022, totalling approximately 946,000 flights, with an average passenger load factor of 83%. Nearly 122.5 million passengers were carried during the year, a result also attributed to the contribution of highly qualified employees. By the end of 2023, the Lufthansa Group employed nearly 100,000 staff members (Lufthansa Group, 2025).

4.2 Historical events in airline industry

Throughout its history, Deutsche Lufthansa Group has undergone significant transformations, mainly driven by external factors. They have inevitably influenced the volatility of its stock prices. In the years 2007–2008, Lufthansa Group performed very well, establishing a stable revenue base through strategic investment in fleet expansion, penetration of the Asian market, and diversification into technical services (Lufthansa Technik) and in-flight catering (LSG Sky Chefs).

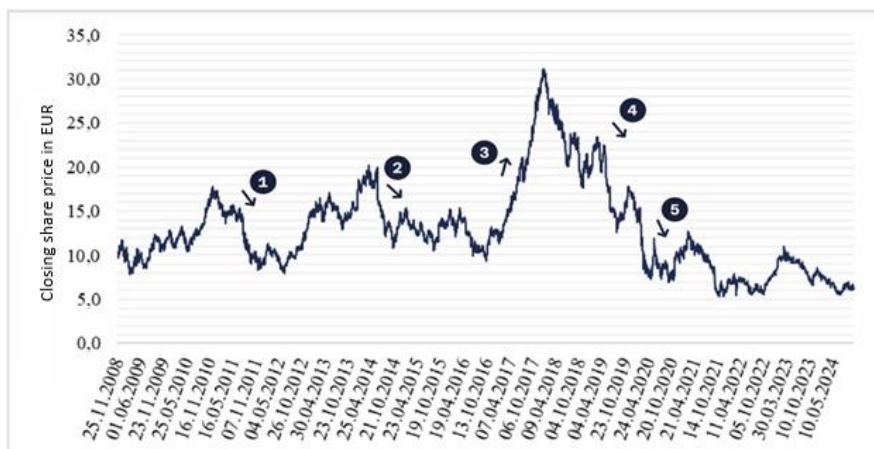


Figure 3. Historical events influencing the price trend of Deutsche Lufthansa Group shares (2008–2024)

In 2008, Lufthansa acquired a 45% share in Brussels Airlines for EUR 65 million, with an option to purchase the remaining 55% by 2011. This strategic move boosted the company's share price (dw.com, 2008). At the end of 2008, however, the Global financial crisis hit the industry, leading to the implementation of stabilization mechanisms. In 2009, Lufthansa bought Austrian Airlines, which had been long struggling with financial losses, and took over 100% share in Brussels Airlines. The European debt crisis in 2009 led to a 4.5% decline in GDP, contributing to a decrease in air traffic and drop in the share price.

In 2010, operational costs increased as a result of political unrest in the Middle East and North Africa, which negatively affected the airline industry and drove up oil prices. The escalation of the European debt crisis in 2011 further impacted investor confidence, leading to a decline in Lufthansa's market value. In 2012, Lufthansa divested its unprofitable BMI subsidiary, signalling a shift in corporate strategy.

In 2014–2015, government strikes significantly affected the level of Lufthansa's operating costs and profits due to the cancellation of thousands of flights. In 2015, the tragic crash of Germanwings 9525 caused further decline in public confidence and led to a decrease in share prices. In response, Lufthansa implemented a two-person cockpit rule and further invested in enhanced safety technologies.

In 2017, Lufthansa acquired parts of the bankrupt Air Berlin, enabling further expansion and helping the Group achieve the highest passenger traffic in its history (Lufthansa Group, 2018). However, in 2018, the company reported losses attributed to frequent flight delays and rising fuel prices, both of which contributed to another decrease in share prices.

In 2019, Lufthansa faced increasing competition from low-cost carriers and growing pressure to reduce CO2 emissions. However, the company maintained solid performance due to the partial sale of its LSG Group division (Lufthansa Group, 2018). At the beginning of 2020, the demand for global air travel was disrupted significantly by the COVID-19 pandemic, resulting in an 80% decline in revenue. Lufthansa accepted a bailout package from the German government, amounting to EUR 9 billion, which enabled the company to navigate this challenged period (Lufthansa Group, 2018).

The Russia-Ukraine war conflict in 2022 caused another decline in the demand, while the closure of Russian airspace significantly affected several travel routes (Lufthansa Group, 2025). In 2023, Lufthansa sold the remaining share of LSG division and continued to invest in profitability and fleet modernization.

In 2024, Lufthansa faced challenges including inflation, high fuel prices, employee strikes, and ongoing investments in modernization. Despite these challenges, the company started a comprehensive recovery program aimed at strengthening its long-term market position (Lufthansa Group, 2025). In 2025, Lufthansa's share price is expected to rise, supported by the anticipated integration of the Italian airline ITA Airways into the group.

4.3 Descriptive statistics

This chapter presents the basic statistical characteristics of the input data used for the application of a neural network method. The descriptive statistics are provided in the graphical form in Figure 4.

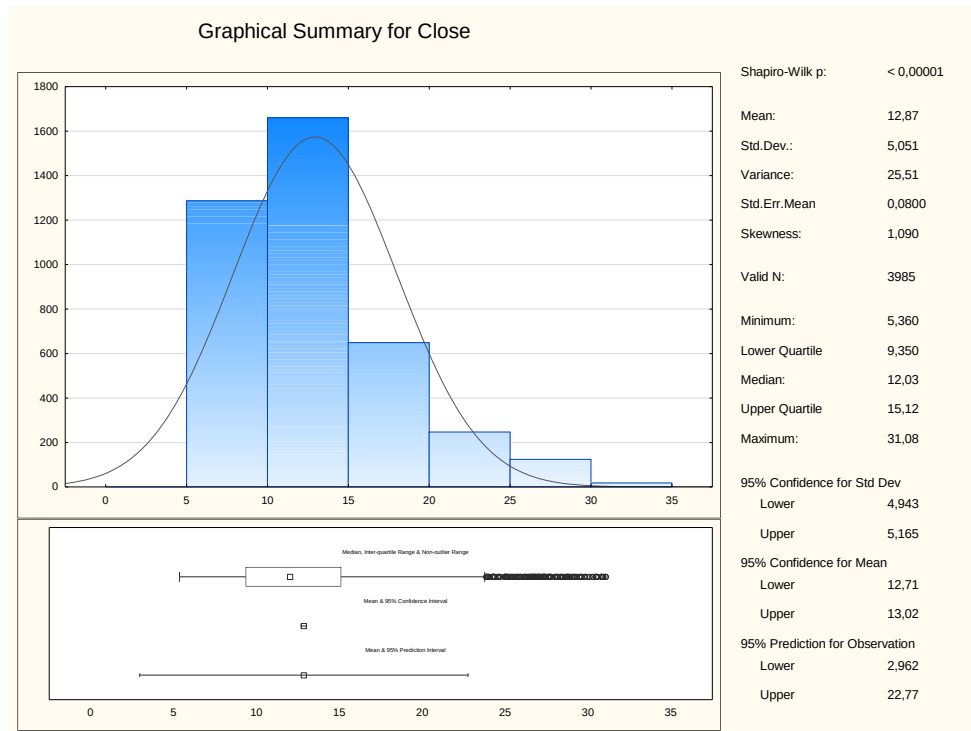


Figure 4. Basic statistical characteristics of share price trend (LHAG, 2008–2024)

The histogram illustrates the trend in stock prices by distributing the data into intervals. The red curve in the histogram represents the Gaussian (normal) distribution curve. The highest point of this curve corresponds to the mode, which denotes the most frequently occurring value in the dataset. The curve highlights the difference between the empirical distribution and the theoretical distribution of the data. In the case of a perfectly normal distribution, the blue bars would align closely with the red curve; however, this alignment is not observed here due to several deviations in the actual data distribution.

This deviation is further confirmed by the result of the Shapiro–Wilk test of normality (displayed in the top right corner of the figure), where the p-value of < 0.00001 clearly indicates a significant departure from a normal distribution. Beneath the Shapiro–Wilk test result, the descriptive statistics are presented, with the exception of the lower quartile (EUR 9.145) and the upper quartile (EUR 15.43). Below the histogram, a box plot displays the median, interquartile range, potential outliers, confidence intervals, and prediction intervals.

The confidence interval for the standard deviation ranges from EUR 4.943 to EUR 5.165, indicating consistency in the measure of variability. The confidence interval for the median spans from EUR 12.71 to EUR 13.02, suggesting a high level of precision in the estimation of the central value. Lastly, the prediction interval for individual observations ranges from EUR 2.962 to EUR 22.77, reflecting a relatively wide spread and indicating a high degree of price volatility in the stock of the Deutsche Lufthansa Group during the observed period, i.e., from 2008 to 2024.

4.4 Results of artificial neural networks

Table 2 shows the overview of these 10 retained active multilayer perceptron (MLP) network.

Table 2. Overview of retained active neural networks (LHAG, 2008–2024)

Index	Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 1-25-1	0.966973	0.972620	0.964269	0.824041	0.695220	0.922786	BFGS 532	SOS	Tanh	Identity
2	MLP 1-17-1	0.971841	0.978954	0.968999	0.709379	0.540141	0.810222	BFGS 610	SOS	Tanh	Exponential
3	MLP 1-21-1	0.966684	0.970638	0.965497	0.831236	0.744954	0.892612	BFGS 2516	SOS	Logistic	Tanh
4	MLP 1-20-1	0.970775	0.975626	0.971029	0.730699	0.620312	0.752157	BFGS 543	SOS	Tanh	Logistic
5	MLP 1-19-1	0.964500	0.971387	0.963941	0.885894	0.729251	0.931940	BFGS 469	SOS	Tanh	Logistic
6	MLP 1-18-1	0.969092	0.973980	0.966074	0.772227	0.664128	0.877367	BFGS 288	SOS	Tanh	Logistic
7	MLP 1-15-1	0.965880	0.972462	0.964894	0.850829	0.701534	0.906798	BFGS 315	SOS	Tanh	Logistic
8	MLP 1-19-1	0.967008	0.972673	0.965579	0.823165	0.694761	0.889680	BFGS 416	SOS	Tanh	Identity
9	MLP 1-21-1	0.969316	0.973265	0.970117	0.767028	0.679674	0.774082	BFGS 612	SOS	Tanh	Tanh
10	MLP 1-18-1	0.967407	0.972007	0.965002	0.813520	0.710406	0.904582	BFGS 390	SOS	Tanh	Identity

The input layer consists of a single variable, namely the date. The hidden layer contains between 2 and 25 neurons. The output layer also contains a single neuron, representing the closing price of shares. All networks were trained using an optimization algorithm, with the sum of squares (SOS) employed as the error function. Individual retained neural network differ in terms of the activation function applied in both the hidden and output layers. The hidden layer predominantly utilizes the hyperbolic tangent (tanh) activation, and logistic function in one case. For the output layer, 4 different activation functions are used, specifically identity, exponential, hyperbolic tangent, and logistic function. The column presenting the training, testing, and validation performance contains highly important values. The research goal is to identify a network that ideally shows equal performance across all data categories (training, testing, validation) and the lowest possible error. In each category, performance is expressed using the correlation coefficient. The closer the value to 1, the more accurate the networks' predictions are. The neural networks demonstrate very good performance in all three categories, with values ranging from 0.964500 to 0.971841 in the training dataset, from 0.970638 to 0.978954 in the testing dataset, and from 0.963941 to 0.971029 in the validation dataset. There can thus be observed a strong similarity between the individual datasets, which indicates the predictive accuracy of the neural networks. Table 3 provides a detailed overview of the networks' predictive performance statistics in these datasets.

Table 3. Predictive performance statistics of smoothed time series (LHAG, 2008–2024)

Statistics	1.MLP 1-25-1	2.MLP 1-17-1	3.MLP 1-21-1	4.MLP 1-20-1	5.MLP 1-19-1	6.MLP 1-18-1	7.MLP 1-15-1	8.MLP 1-19-1	9.MLP 1-21-1	10.MLP 1-18-1
Minimum prediction (Train)	5.72383	5.37125	4.98089	5.85063	5.55476	5.84385	5.55959	5.74023	4.98524	5.72852
Maximum prediction (Train)	29.08998	29.61810	28.46726	28.48416	27.96875	29.43971	28.07520	29.01453	27.20204	28.86259
Minimum prediction (Test)	5.73585	5.37129	5.07686	5.86763	5.55509	5.84396	5.56520	5.75503	5.07541	5.72832
Maximum prediction (Test)	29.08879	29.57839	28.46681	28.42711	27.96783	29.42026	28.07541	29.01552	27.17961	28.84252
Minimum predic. (Valid.)	5.72436	5.37145	5.01296	5.85077	5.55494	5.86750	5.55955	5.74008	5.01533	5.72857
Maximum predic. (Valid.)	29.02730	29.59689	28.46714	28.47024	27.96080	29.42985	28.05069	29.01263	27.19659	28.85258
Minimum residual (Train)	-3.84272	-3.64551	-4.13171	-4.34414	-4.04813	-3.81815	-4.05297	-3.97776	-4.01865	-4.34243
Maximum residual (Train)	4.41957	4.27349	4.37556	3.99286	4.60042	4.18766	4.59903	4.54461	4.21195	4.38136
Minimum residual (Test)	-2.94660	-2.97540	-3.27082	-3.46885	-3.64287	-3.10277	-3.28550	-2.99464	-3.51444	-2.99962
Maximum residual (Test)	4.19749	4.04609	4.16140	3.77832	4.28850	4.16355	4.38672	4.32639	4.05636	4.16206
Minimum residual (Valid.)	-3.32268	-2.94451	-3.48587	-3.70318	-3.35760	-3.27998	-3.35134	-3.28528	-3.86569	-3.67298
Maximum residual (Valid.)	4.43286	4.29474	4.37698	3.99497	4.48670	4.04098	4.59753	4.55202	3.94275	4.39050
Minimum standard residual (Train)	-4.23316	-4.32832	-4.53176	-5.08200	-4.30094	-4.34491	-4.39392	-4.38424	-4.58854	-4.81447
Maximum standard residual (Train)	4.86862	5.07392	4.79923	4.67105	4.88773	4.76540	4.98592	5.00903	4.80925	4.85763
Minimum standard residual (Test)	-3.53395	-4.04848	-3.78958	-4.40434	-4.26585	-3.80735	-3.92263	-3.59274	-4.26291	-3.55888
Maximum standard residual (Test)	5.03418	5.50531	4.82141	4.79726	5.02189	5.10903	5.23740	5.19048	4.92025	4.93805
Minimum standard residual (Valid.)	-3.45890	-3.27123	-3.68960	-4.26993	-3.47805	-3.50171	-3.51936	-3.48301	-4.39374	-3.86184
Maximum standard residual (Valid.)	4.61460	4.77128	4.63280	4.60638	4.64765	4.31416	4.82802	4.82600	4.48132	4.61625

Thus, Table 3 provides information on the range and accuracy of the predicted values. It also includes the residual values. Ideally, these should be equal to 0, which would indicate perfect agreement between the input data and the resulting predictions. However, the table shows that although the residuals are often close to 0, there are slight deviations, indicating a certain level of inaccuracy in the neural network's predictions. Despite these deviations, the networks perform successfully and are considered capable of predicting closing stock prices with high reliability. This is further illustrated in detail in Figure 5.

The data are divided into training, testing, and validation datasets. The first part of the table presents the results for the minimum and maximum predicted values. For example, the first row of the table shows the minimum predicted values for the training set, ranging from 4.98 to 5.80, while the second row shows the maximum values, ranging from 27.20 to 29.63. Similarly, the table presents the minimum and maximum predicted values for the testing and validation sets. The second part of the table displays the minimum and maximum residuals for the training, testing, and validation datasets in the same way. The final part of the table presents the standardized residuals for each dataset, i.e., normalized deviations between the predicted and actual values using the standard deviation. This standardization helps to detect outliers, which indicate the inaccuracy of individual MLP networks in their predictions.

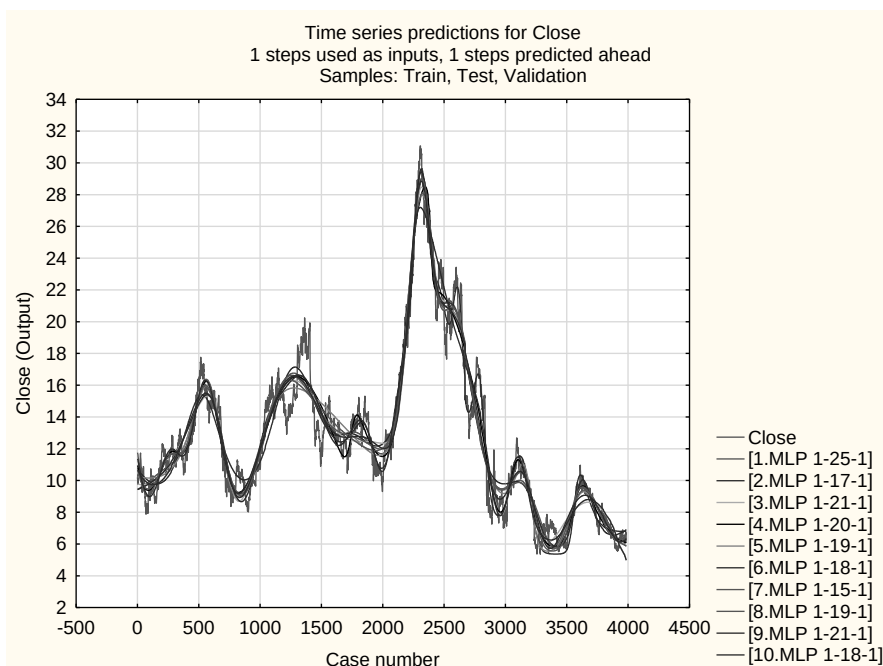


Figure 5. Share price trend predicted using neural networks (LHAG, 2008–2024)

Figure 5 shows the smoothed time series of historical closing share prices in the monitored period 2008–2024. The blue curve represents the actual development of share prices, while the other differently coloured curves depict the development of prices as predicted by the ten retained MLP networks. It should be emphasized that this is not a forecast of future prices, but rather a record of how well each network was able to reconstruct the known historical values in comparison with the actual data. The resulting residuals are shown in more detail in Figure 6. As illustrated in the graph, the retained networks performed very well and were able to replicate the actual stock price development with a high degree of accuracy. Although some deviations can be observed at local maxima and minima between the actual and predicted values of individual networks, these discrepancies should not significantly affect the overall reliability of the prediction. The historical development of stock prices over the years demonstrates considerable volatility. The share price reached its peaks in the years 2010 (value 500), 2014 (value 1,500), and 2017 (value 2,400), while notable troughs occurred in more recent years, specifically in 2021 (value 3,250) and 2024 (value 4,000).

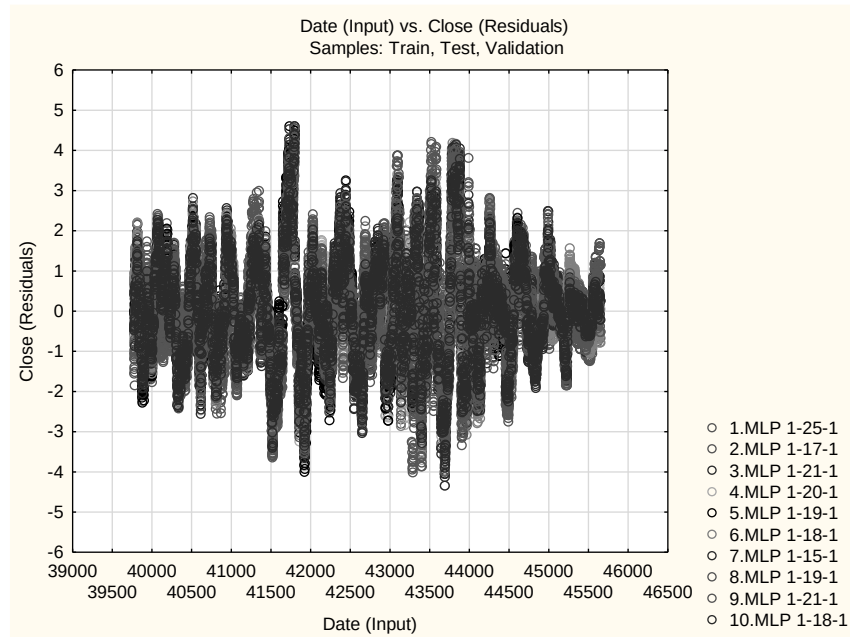


Figure 6. Graph of historical data residuals (LHAG, 2008–2024)

Figure 6 displays the residuals between the actual share price and the values predicted by the 10 retained neural networks. The horizontal (x) axis represents the date, while the vertical (y) axis shows the residual values. Ideally, the values of individual residuals should be as close to zero as possible, indicating minimal deviation between predicted and actual prices. However, the neural networks do not achieve perfect accuracy in some cases. This is evident from values that deviate either positively or negatively from zero. The largest residual deviations are observed particularly between the years 2013 and 2014 (values ranging from 41,500 to 42,000) and during the period from 2017 to 2020 (values between 43,000 and 44,000). In these intervals, the residuals vary within the range of approximately -4 to 5 and -4 to 0. During the rest of the monitored period, the values are concentrated around the desired value of zero, mostly within the -2 to 2 range, which indicates very good prediction accuracy. The performance of individual MLP networks could be seen in Figure 7.

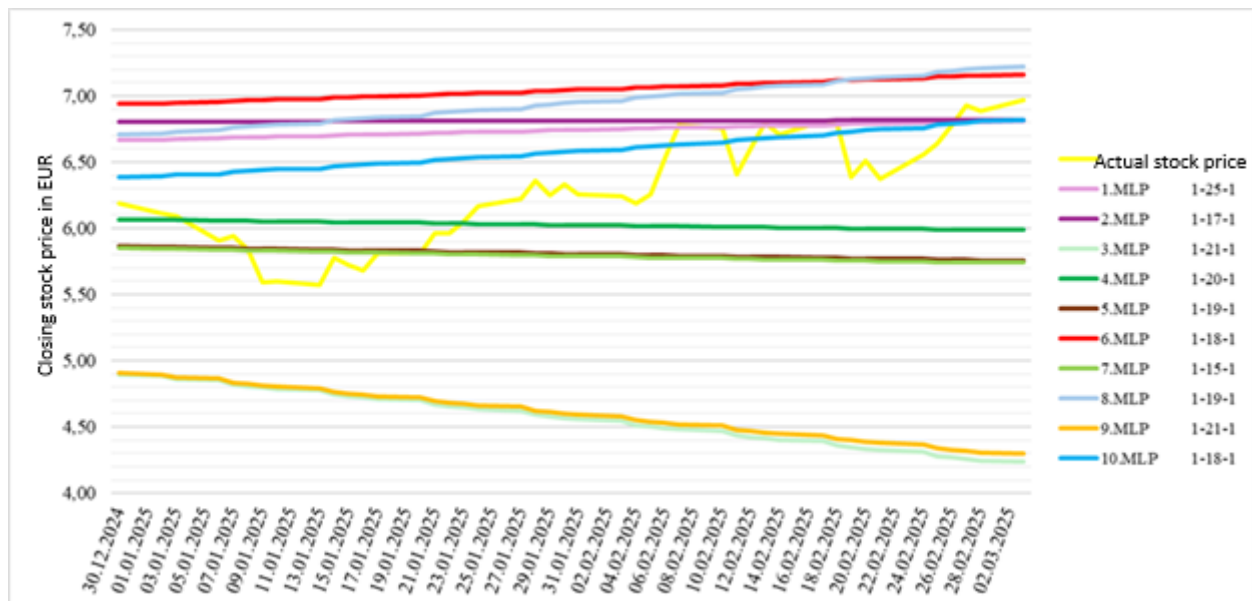


Figure 7. Predicted closing price of Lufthansa Group's stock by MLP networks

Figure 7 illustrates the short-term forecast of the closing share price of the Lufthansa Group airline, covering the period from 30 December 2024 to 3 March 2025. As seen in the graph, the yellow curve represents the actual closing price of LHAG shares as recorded on the German stock exchange (Cboe Europe Equities) during the observed period. The remaining differently coloured curves display the predicted values over the same period, as generated by the 10 retained MLP networks. The actual share price ranged between EUR 5.50 and 6.50 from 30 December 2024 until 6 February 2025, when it first exceeded the upper bound of this interval. From that point onward, the price followed an upward trend—with minor fluctuations—reaching its peak of EUR 6.97 on 3 March 2025. Conversely, the lowest recorded value during the analysed period was EUR 5.57, observed on 13 January 2025. As can be seen from the figure, the actual development of the closing share price of Lufthansa Group did not exhibit any significant volatility over the monitored timeframe.

The figure shows that the orange and peppermint curves corresponding to 3.MLP and 9.MLP networks exhibit a markedly decreasing trend and a trajectory that significantly diverges from the actual development of the share price. As such, these networks appear to be the least accurate. Only the brown and light green curves, representing the 5.MLP and 7.MLP networks, indicate a slightly declining trend, whereas the remaining networks generally follow an upward trajectory. In contrast, the purple, red, and light blue curves (2.MLP, 6.MLP, and 8.MLP networks) approximate the accurate trend of the share price. However, they predict excessively high share prices ranging from EUR 6.67–7.22, which constitutes a notable deviation from the actual closing prices. As seen in the graph, the dark blue curve (10.MLP network) best captures the closing price, accurately reflecting both the trend and direction of the actual share price. The pink and dark green curves (1.MLP and 4.MLP networks) also performed well, displaying only minor deviations from the actual price trend. The three most accurate MLP networks are displayed in detail in Figure 8.

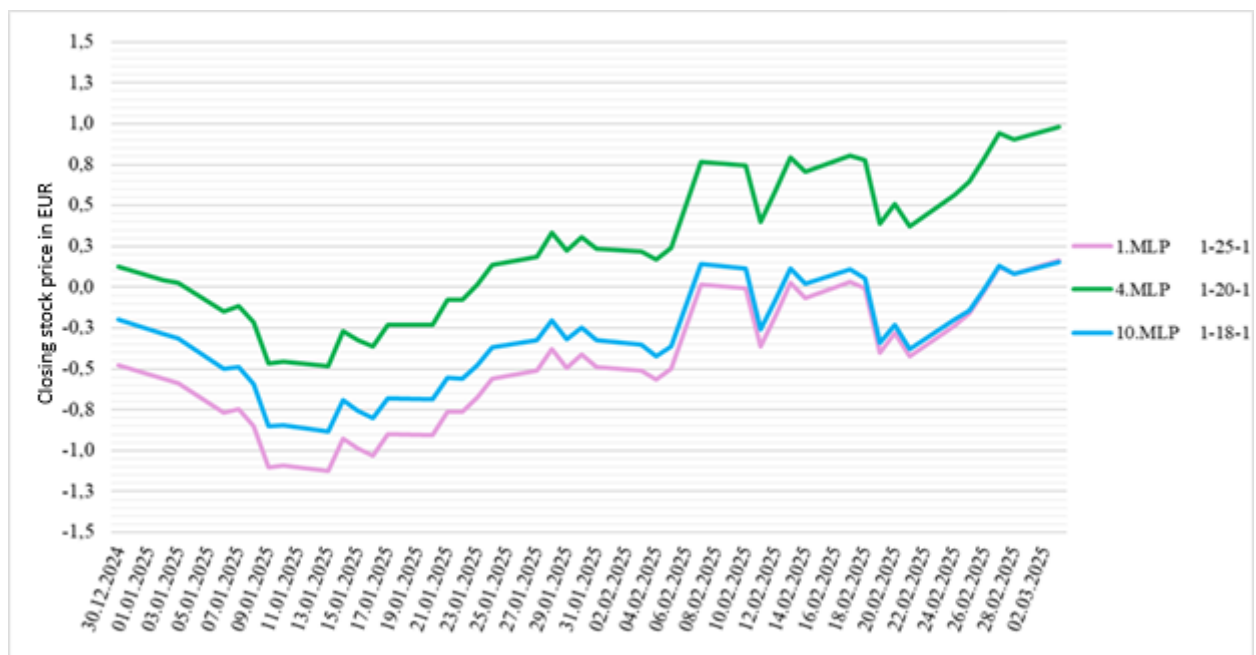


Figure 8. Residual graph of the closing share price prediction for Lufthansa Group by MLP networks

Figure 8 presents the three most accurate neural networks predicting the share prices of the Lufthansa Group. The most suitable MLP network is the one with the average residual closest to zero, which indicates a perfect match with the actual share price. The most accurate model is MLP network No. 10, which demonstrates an average residual value of 0.3579, representing a highly satisfactory result. The smallest residuals observed for this network are -0.011, 0.019, and 0.057, while the largest residuals reach -0.881, -0.849, and -0.845. The median residual is 0.3210. This network thus provides the most stable prediction with the smallest deviations from the actual price and is considered the most suitable for predicting the closing share price of the Lufthansa Group. The second most accurate network is MLP network No. 4, which yields an average residual of 0.4070. The smallest residuals for this model are 0.015, 0.027, and 0.044, while the largest reach 0.983, 0.940, and 0.940.

0.902. The third most accurate model is MLP network No. 1, with an average residual of 0.4884. It shows extremely small residuals of -0.005, -0.006, and 0.017, which are very close to zero. However, its largest residuals exceed the value of -1, specifically -1.126, -1.101, and -1.094, indicating a relatively significant divergence. It is evident that residuals can be both positive and negative, as they merely represent the difference between the predicted and actual values – i.e., the distance from zero. The graph also shows that all three top-performing networks exhibit an initial downward trend followed by an upward trend, which mirrors the actual share price movement. An interesting observation is that the largest residuals for all three MLP networks occur on consecutive trading days.

5. Discussion

The aviation industry is a dynamic sector that must be able to adapt to rapid changes in the needs of modern society. With the growing popularity of air travel, expectations regarding service quality, comfort, and reliability are increasing. Due to geopolitical crises, technological advancements, and globalization, airlines are under pressure, and their management must effectively respond to changes and challenges in the macroeconomic environment while simultaneously modernizing services, fleet, and staff training. These transformations affect both air carriers and the development of their share prices.

Based on the results obtained from graphical analysis, document analysis, time series analysis, and artificial neural networks, it is possible to answer the formulated research questions.

To address RQ1, which examines the factors influencing the volatility of Deutsche Lufthansa Group's share price, historical data were analysed along with the identification of the key factors that had the greatest impact on the development of share prices in the period 2004–2024. The most significant influences include external shocks, such as the COVID-19 pandemic, which led to a considerable decline in the demand for air transport and a subsequent drop in Lufthansa's share prices in 2020–2022. However, this decline was mitigated by Lufthansa's rapid response to the crisis and utilization of government bailout, while some of its competitors were more severely affected.

Another significant external factor was the 2008 global financial crisis and its consequences, including the European debt crisis, which led to an increase in operating costs, a decline in demand, and a general deterioration of the economic environment, subsequently influencing the volatility of Lufthansa's share prices. The rising fuel prices in the years 2011–2012 and 2018 also contributed to increased volatility in Lufthansa's stock performance; however, fuel hedging contracts helped mitigate fluctuations in the case of low-cost carriers.

Internal factors influencing the volatility of share prices include employee strikes, particularly the major actions in the years 2014–2015 and again in 2024, which directly affected operational costs and investor confidence. The implementation of a new corporate strategy also had an impact on the volatility of Lufthansa's share price. The significance of these factors is supported by studies such as Vochozka et al. (2022), which demonstrate that share price movements are influenced not only by macroeconomic variables, but also by internal factors such as corporate strategy, organizational restructuring, or acquisitions.

To address the R2, a prediction method based on multilayer perceptron neural networks was used to forecast the development of share prices of Deutsche Lufthansa Group for January and February 2025. The network with the lowest average residuals from actual values was selected, indicating minimal deviations between predicted and observed data. The results indicate that the expected development of Lufthansa's share price is likely to follow a slightly upward and stable trend. The forecast begins at EUR 6.39 and rises to EUR 6.82 by the end of February, suggesting positive expectations and cost stabilisation.

Based on these findings, it can be stated that the application of MLP neural networks is an effective method for forecasting the stock performance of Deutsche Lufthansa Group. However, as noted by Gite et al. (2021) and Zheng et al. (2021), prediction remains challenging in a turbulent market environment.

Conclusions

Nowadays, events that disrupt the stability of the global economy and financial markets occur with increasing frequency. Geopolitical uncertainty, pandemics, oil or fuel price fluctuations, and changes in legislation drive investors to reassess the potential of various sectors, including aviation, which is one of the most sensitive sectors. The aviation industry also offers attractive investment opportunities, which increases the demand for tools for predicting stock price and stability analysis.

The aim of the paper was to examine the development of Deutsche Lufthansa Group's share prices, analyse the corresponding time series, and predict price trends for January and February 2025. To achieve this goal, historical daily price data for the period 2004–2024 were used to identify trends, fluctuations, and key factors influencing the volatility of share prices. The future trend was predicted using multilayer perceptron networks implemented in the Statistica software. Through graphical analysis, time series analysis, document analysis, and time series analysis, the study identified both external and internal factors affecting price development. Based on these analyses, a forecast of the expected share price trend for Deutsche Lufthansa Group was produced.

The results revealed that the prediction for Lufthansa's share prices show a slightly upward and stable trend, beginning at EUR 6.39 and rising to EUR 6.82 by the end of February 2025. This trend reflects the positive expectation and stabilization of costs, which may indicate renewed investor confidence in the company's long-term recovery.

The objective of the paper was successfully met. All research questions were addressed, and the desired outcomes in analysing and predicting the share price development were achieved. The research limitations included the restricted availability of historical data for Deutsche Lufthansa Group, particularly from the year 2008, which constrained the scope of the analysis. Additionally, limitations related to the short time horizon of the forecast. Further research could broaden the analysis to include a larger sample of airlines and extend the prediction period, which would allow for the consideration of long-term trends and fluctuations, enhancing the accuracy of forecasts and supporting strategic planning in the aviation industry.

References

- Adeniran, A. O., Stephens, M. S., & Njoku, I. (2023). Assessment of basic airline service in Nigeria. *Insights into Regional Development*, 5(2), 38-59. [https://doi.org/10.9770/ird.2023.5.2\(3\)](https://doi.org/10.9770/ird.2023.5.2(3))
- Azzolina, S., Razza, M., Sartiano, K., & Weitschek, E. (2021). Price discrimination in the online airline market: An empirical study. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(6), 2282-2303. <https://doi.org/10.3390/jtaer16060126>
- Barra, S., Carta, S. M., Corrigan, A., Podda, A. S., & Recupero, D. R. (2020). Deep learning and time series-to-image encoding for financial forecasting. *IEEE/CAA Journal of Automatica Sinica*, 3, 683-692. <https://doi.org/10.1109/JAS.2020.1003132>
- Chi, D. J., & Shen, Z. D. (2022). Using hybrid artificial intelligence and machine learning technologies for sustainability in going-concern prediction. *Sustainability*, 14(3), 1810. <https://doi.org/10.3390/su14031810>
- Choi, K., & Choi, J. (2023). A Study of Prediction of Airline Stock Price through Oil Price with Long Short-Term Memory Model. *International Journal of Advanced Computer Science and Applications*, 14(5), 154-160. <https://doi.org/10.14569/IJACSA.2023.0140509>
- Deb, S. G. (2021). Analyzing airlines stock price volatility during COVID-19 pandemic through internet search data. *International Journal of Finance & Economics*, 28(2), 1497-1513. <https://doi.org/10.1002/ijfe.2490>
- Domínguez-CC, M., Casanueva, C., & Gallego, A. (2021). Tourist destinations and cooperative agreements between airlines. *Journal of Destination Marketing & Management*, 20. <https://doi.org/10.1016/j.jdmm.2021.100613>
- Drammeh, F. Y. (2024). Managing tourism during the COVID-19 pandemic: A systematic review of crisis management in the tourism industry. *Cogent Social Sciences*, 10(1), 2311955. <https://doi.org/10.1080/23311886.2024.2311955>

- Gabor, M. R., Kardos, M., & Oltean, F. D. (2022). Yield management—a sustainable tool for airline e-commerce: Dynamic comparative analysis of e-ticket prices for Romanian full-service airline vs. low-cost carriers. *Sustainability*, 14(22). <https://doi.org/10.3390/su142215150>
- Gite, S., Khatavkar, H., Kotecha, K., Srivastava, S., Maheshwari, P., & Pandey, N. (2021). Explainable stock prices prediction from financial news articles using sentiment analysis. *Computer Science*, 340. <https://doi.org/10.7717/peerj-cs.340>
- Google Finance. (2024). CZ Lufthansa. Retrieved April 25, 2025, from <https://www.google.com/finance/quote/LHA:ETR>
- Harvey, G., & Turnbull, P. (2020). Ricardo flies Ryanair: Strategic human resource management and competitive advantage in a single European aviation market. *Human Resource Management Journal*, 4, 553-565. <https://doi.org/10.1111/1748-8583.12315>
- Investing.com. (2025). Deutsche Lufthansa AG (LHAd). Retrieved April 25, 2025, from <https://www.investing.com/equities/dt-lufthansa-historical-data?cid=33048>
- Jayaram, A., Amit, R. K., Agarwal, A., & Luo, X. D. (2023). Elasticity-integrated pricing and allocation heuristic for airline revenue management. *Journal of Revenue and Pricing Management*, 23, 305-317. <https://doi.org/10.1057/s41272-023-00454-6>
- Katina, J., Katin, I., & Komarova, V. (2024). Cryptocurrency price forecasting: a comparative analysis of autoregressive and recurrent neural network models. *Entrepreneurship and Sustainability Issues*, 11(4), 425-436. [https://doi.org/10.9770/jesi.2024.11.4\(26\)](https://doi.org/10.9770/jesi.2024.11.4(26))
- Khan, W., Ghazanfar, M. A., Azam, M. A., Karami, A., Alyoubi, K. H., & Alfakeeh, A. S. (2020). Stock market prediction using machine learning classifiers and social media, news. *Journal of Ambient Intelligence and Humanized Computing*, 13, 3433-3456. <https://doi.org/10.1007/s12652-020-01839-w>
- Lufthansa Group. (2018). *Annual report 2017* [online]. Retrieved April 25, 2025, from <https://investor-relations.lufthansagroup.com/fileadmin/downloads/en/financial-reports/annual-reports/LH-AR-2017-e.pdf>
- Lufthansa Group. (2020). *Annual report 2019* [online]. Retrieved April 25, 2025, from <https://investor-relations.lufthansagroup.com/fileadmin/downloads/en/financial-reports/annual-reports/LH-AR-2019-e.pdf>
- Lufthansa Group. (2025). *Annual report 2024* [online]. Retrieved April 25, 2025, from <https://investor-relations.lufthansagroup.com/fileadmin/downloads/en/financial-reports/annual-reports/LH-AR-2024-e.pdf>
- Nabipour, M., Nayyer, P., Jabani, H., Mosavi, A., Salwana, E., & Shahab, S. (2020). Deep learning for stock market prediction. *Entropy*, 22 (8). <https://doi.org/10.3390/e22080840>
- Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2021). A novel multi-source information-fusion predictive framework based on deep neural networks for accuracy enhancement in stock market prediction. *Journal of Big Data*, 1. <https://doi.org/10.1186/s40537-020-00400-y>
- Oliveira, A. V. M., Caliori, T., & Narcizo, R. R. (2022). An empirical model of fleet modernization: On the relationship between market concentration and innovation adoption by airlines. *Research in Transportation Business & Management*, 43. <https://doi.org/10.1016/j.rtbm.2021.100704>
- Oliveira, A. V. M., Narcizo, R. R., Caliori, T., Morales, M. A. V., & Pardo, R. (2021). Estimating fuel-efficiency while accounting for dynamic fleet management: Testing the effects of fuel price signals and fleet rollover. *Transportation Research Part D: Transport and Environment*, 95. <https://doi.org/10.1016/j.trd.2021.102820>
- Penela, D., & Palma, M. (2023). Risk factor disclosures in the US airline industry following the COVID-19 pandemic. *Risks*, 11(2), 34. <https://doi.org/10.3390/risks11020034>
- Peternel, E., & Bukvič, V. (2024). Assessment of investment returns through the prism of investment strategies: comparison of performance of the most successful investors and the Slovenian funds. *Entrepreneurship and Sustainability Issues*, 12(2), 31-52. <https://doi.org/10.9770/e4338524934>
- Pietreanu, C. V., Zaharia, S. E., & Munteanu, A. R. (2019). Trends in airline business models. *New Trends in Sustainable Business and Consumption – BASIQ International Conference*, 499-506. <https://conference.ase.ro/papers/2019/19065%20-%20Pietreanu.pdf>
- Ramezani, R., Peymanfar, A., & Ebrahimi, S. B. (2019). An integrated framework of genetic network programming and multi-layer perceptron neural network for prediction of daily stock return: An application in Tehran stock exchange market. *Applied Soft Computing*, 82. <https://doi.org/10.1016/j.asoc.2019.105551>
- Sonkavde, G., Dharrao, D. S., Bongale, A. M., Deokate, S. T., Doreswamy, D., & Bhat, S. K. (2023). Forecasting stock market prices using machine learning and deep learning models: A systematic review, performance analysis and discussion of implications. *International Journal of Financial Studies*, 11(3), 94. <https://doi.org/10.3390/ijfs11030094>

Šuleř, P., & Machová, V. (2020). Better results of artificial neural networks in predicting ČEZ share prices. *Journal of International Studies*, 13(2), 259-278. <https://doi.org/10.14254/2071-8330.2020/13-2/18>

Sustainalytics. (2024). *Deutsche Lufthansa AG*. Retrieved April 25, 2025, from <https://www.sustainalytics.com/esg-rating/deutsche-lufthansa-ag/1008288398>

Thorbecke, W. (2020). The impact of the COVID-19 pandemic on the U.S. economy: Evidence from the stock market. *Journal of Risk and Financial Management*, 13(10), 233. <https://doi.org/10.3390/jrfm13100233>

Valido, J., Socorro, M. P., & Medda, F. (2020). Airport capacity and entry deterrence: Low cost versus full service airlines. *Economics of Transportation*, 22. <https://doi.org/10.1016/j.ecotra.2020.100165>

Vijh, M., Chandola, D., Tikkiwal, V. A., & Kumar, A. (2020). Stock closing price prediction using machine learning techniques. *Procedia Computer Science*, 167, 599-606. <https://doi.org/10.1016/j.procs.2020.03.326>

Vochozka, M., Novotná, L., & Hovanec, M. (2022). The importance of sentiment in evaluation of corporate bond price. *Transformations in Business & Economics*, 21(2B). <https://www.transformations.knf.vu.lt/56b/article/theipo>

Wang, J., & Li, A. (2023). Design of enterprise financial performance prediction model based on artificial intelligence algorithm. *Soft Computing*, 28. <https://doi.org/10.1007/s00500-023-08516-y>

Wang, S., Zhang, S., Xi, G., & Wong, M. C. (2024). Analysis of innovation efficiency and influencing factors of listed companies in Beijing-Tianjin-Hebei economic zone based on improved DEA. *Insights into Regional Development*, 6(2), 24-47. [https://doi.org/10.9770/ird.2024.6.2\(2\)](https://doi.org/10.9770/ird.2024.6.2(2))

Xu, Z., Zhang, R., McGrory, C. A., Wu, M., & Wang, J. (2023). Forecasting stock closing prices with an application to airline company data. *Data Science and Management*, 6, 239-246. <https://doi.org/10.1016/j.dsm.2023.09.005>

Zheng, L. Y., & He, H. M. (2021). Share price prediction of aerospace relevant companies with recurrent neural networks based on PCA. *Expert Systems with Applications*, 183. <https://doi.org/10.1016/j.eswa.2021.115384>

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Ing. Jakub HORÁK, MBA, PhD. works as a Deputy Director for Research and Development at the School of Expertness and Valuation at the Institute of Technology and Business in České Budějovice, where he teaches and researches in the field of business economics and corporate finance. He is also the executive director of the Institute of Technology and Business in Prešov. His professional interest focuses primarily on the issues of financial stability of enterprises, pricing and effective use of corporate resources in the conditions of a changing economic environment. In his extensive publishing activity, he focuses on issues of sustainable business and modern approaches to managing economic processes, both at the microeconomic and macroeconomic levels. He actively participates in solving many national and international research projects focused on innovations in the field of business economics and cooperates with professional practice with the aim of connecting academic knowledge with the needs of the business sector.

ORCID ID: <https://orcid.org/0000-0001-6364-9745>